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TECHNIQUES BASED ON ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS (ANFIS) FOR ESTIMATING AND EVALUATING PHYSICAL DEMANDS AT WORK USING HEART RATE

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Cette thèse intitulée:

TECHNIQUES BASED ON ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS (ANFIS) FOR ESTIMATING AND EVALUATING PHYSICAL DEMANDS AT WORK USING HEART RATE

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en vue de l'obtention du diplôme de : Philosophiae Doctor

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DEDICATION

To my lovely mother, Mrs. Emine Yalcin

To my uncle, Dr. Umar Al-Turki

To all my family members

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First of all, I am very thankful to God, who has empowered me with his guidance throughout my life. I am thankful to God for giving me the patience and perseverance to overcome difficulties through this journey and achieve my dream.

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RÉSUMÉ

Malgré l'évolution rapide de la mécanisation dans les industries lourdes, les emplois physiquement exigeants qui nécessitent un effort humain excessif représentent encore une part importante dans de nombreuses industries (foresterie, construction, mines, etc.). Des études ont montré que les charges de travail excessives imposées aux travailleurs sont la principale cause de fatigue physique, ce qui a des effets négatifs sur les travailleurs, leur performance et la qualité du travail. Par conséquent, les chercheurs ont souligné l'importance de la conception optimale des tâches (à l'intérieur des compétences des travailleurs) afin de maintenir la sécurité, la santé et la productivité des travailleurs. Toutefois, cela ne peut être atteint sans comprendre (c'est-à-dire mesurer et évaluer) les exigences physiologiques du travail. À cet égard, les trois études comprises dans cette thèse présentent des approches pratiques pour estimer et évaluer la dépense énergétique (DE), exprimée en termes de consommation d'oxygène (VO_2), au cours du travail réel.

La première étude présente de nouvelles approches basées sur le système d'inférence neuro-flou adaptatif (ANFIS) pour l'estimation de la VO_2 à partir des mesures de la fréquence cardiaque (FC). Cette étude comprend deux étapes auxquelles ont participé 35 individus en bonne santé. Dans un premier temps, deux modèles novateurs individuels ont été développés en se basant sur l'ANFIS et les méthodes analytiques. Ces modèles s'attaquent au problème de l'incertitude et de la non-linéarité entre la FC et la VO_2. Dans un deuxième temps, un modèle général ANFIS qui ne requiert pas d'étalonnage individuel a été développé. Les trois modèles ont été testés en laboratoire et sur le terrain. La performance de chaque modèle a été évaluée et comparée aux VO_2 mesurées et à deux méthodes d'estimation individuelles et traditionnelles de VO_2 (étalonnage linéaire et Flex-HR). Les résultats ont indiqué la précision supérieure obtenue avec la modélisation ANFIS individualisée (EMQ = 1,0 à 2,8 ml/kg.min en laboratoire et sur le terrain, respectivement). Le modèle analytique a surpassé l'étalonnage linéaire traditionnel et les méthodes Flex-HR avec des données terrain. Les estimations du modèle général ANFIS de la VO_2 ne différaient pas significativement des mesures réelles terrain VO_2 (EMQ = 3,5 ml/kg.min). Avec sa facilité d'utilisation et son faible coût de mise en œuvre, le modèle général ANFIS montre du potentiel pour remplacer n'importe laquelle des méthodes traditionnelles individualisées pour l'estimation de la VO_2 à partir de données recueillies sur le terrain.

La deuxième étude présente un modèle de prédiction de la VO_2 basé sur ANFIS qui est inspiré de la méthode Flex-HR. Des études ont montré que la méthode Flex-HR est une des méthodes les plus précises pour l'estimation de la VO_2. Toutefois, cette méthode est basée sur quatre paramètres qui sont déterminés individuellement et par conséquent ceci est considéré comme coûteux, chronophage et souvent peu pratique, surtout lorsque le nombre de travailleurs augmente. Le modèle prédictif proposé se compose de trois modules ANFIS pour estimer les paramètres de Flex-HR. Pour chaque module ANFIS, la sélection de variables d'entrée et le modèle d'évaluation ont été simultanément réalisés à l'aide de la combinaison de la technique de division des données en trois parties et la technique de validation croisée. La performance de chaque module ANFIS a été testée et comparée avec les paramètres observés ainsi qu'avec les modèles de Rennie et coll. (2001) à l'aide de données de test indépendant. En outre, les performances du modèle global de prédiction ANFIS dans l'estimation de la VO_2 a été testé et comparé avec les valeurs mesurées de la VO_2, la méthode de Flex-HR standard ainsi qu'avec les autres modèles généraux (c.-à-d., les modèles de Rennie et coll. (2001) et de Keytel et coll. (2005)). Les résultats n'ont indiqué aucune différence significative entre les paramètres observés et estimés de Flex-HR et entre la VO_2 mesurée et estimée dans la plage de fréquence cardiaque globale et séparément dans différentes gammes de FC. Le modèle de prédiction ANFIS (EMA = 3 ml/kg.min) a montré de meilleures performances que les modèles de Rennie et coll. (EMA = 7 ml/kg.min) et les modèles de Keytel et coll. (EMA = 6 ml/kg.min) et des performances comparables avec la méthode standard de Flex-HR (EMA = 2,3 ml/kg.min) tout au long de la plage de fréquence cardiaque. Le modèle ANFIS fournit ainsi aux praticiens une méthode pratique, économique et rapide pour l'estimation de la VO_2 sans besoin d'étalonnage individuel.

La troisième étude présente une nouvelle approche basée sur l'ANFIS pour classer les travaux en quatre classes d'intensité (c'est-à-dire, très léger, léger, modéré et lourd) à l'aide du monitorage du rythme cardiaque. La variabilité intra-individuelle (différences physiologiques et physiques) a été examinée. Vingt-huit participants ont effectué le test de la montée des marches Meyer et Flenghi (1995) et le test maximal sur le tapis roulant pendant lesquels la fréquence cardiaque et la consommation d'oxygène ont été mesurées. Les résultats ont indiqué que le monitorage du rythme cardiaque (FC, FC max et FC repos) et du poids corporel sont des variables significatives pour classer le rythme de travail. Le classificateur ANFIS a montré une sensibilité, une spécificité et une exactitude supérieures par rapport à la pratique courante à l'aide de catégories de rythme de travail basées sur le pourcentage de fréquence cardiaque de réserve (% FCR), avec une différence globale de 29,6 % dans la précision de classification entre les deux méthodes et un bon équilibre entre la sensibilité (90,7 %, en moyenne) et la spécificité (95,2 %, en moyenne). Avec sa facilité de mise en œuvre et sa mesure variable, le classificateur ANFIS montre un potentiel pour une utilisation généralisée par les praticiens pour évaluation du rythme de travail.

ABSTRACT

Despite the rapid evolution of mechanization in heavy industries, physically demanding jobs that require excessive human effort still represent a significant part of many industries (e.g., forestry, construction, mining etc.). Studies have shown that excessive workloads placed on workers are the main cause of physical fatigue, which has negative effects on the workers, their performance and quality of work. Therefore, researchers have emphasized on the importance of the optimal job design (within workers' capacity) in order to maintain workers' safety, health and productivity. However, this cannot be achieved without understanding (i.e., measuring and evaluating) the physiological demands of work. In this respect, the three studies comprising this dissertation present practical approaches for estimating and evaluating energy expenditure (EE), expressed in terms of oxygen consumption (VO_2), during actual work.

The first study presents new approaches based on adaptive neuro-fuzzy inference system (ANFIS) for the estimation of VO_2 from heart rate (HR) measurements. This study comprises two stages in which 35 healthy individuals participated. In the first stage, two novel individual models were developed based on the ANFIS and the analytical methods. These models tackle the problem of uncertainty and nonlinearity between HR and VO_2. In the second stage, a General ANFIS model was developed which does not require individual calibration. The three models were tested under laboratory and field conditions. Performance of each model was evaluated and compared to the measured VO_2 and two traditional individual VO_2 estimation methods (linear calibration and Flex-HR). Results indicated the superior precision achieved with individualized ANFIS modeling (RMSE= 1.0 and 2.8 ml/kg.min in laboratory and field, respectively). The analytical model outperformed the traditional linear calibration and Flex-HR methods with field data. The General ANFIS model's estimates of VO_2 were not significantly different from actual field VO_2 measurements (RMSE= 3.5 ml/kg.min). With its ease of use and low implementation cost, the General ANFIS model shows potential to replace any of the traditional individualized methods for VO_2 estimation from HR data collected in the field.

The second study presents an ANFIS-based VO_2 prediction model that is inspired by the Flex-HR method. Studies have shown that the Flex-HR method is one of the most accurate methods for VO_2 estimation. However, this method is based on four parameters that are determined individually and therefore it is considered costly, time consuming and often impractical, especially when the number of workers increases. The proposed prediction model

consists of three ANFIS modules for estimating the Flex-HR parameters. For each ANFIS module, input variables selection and model assessment were simultaneously performed using the combination of three-way data split and cross-validation techniques. The performance of each ANFIS module was tested and compared with the observed parameters as well as with Rennie et al.'s (2001) models using independent test data. In addition, the performance of the overall ANFIS prediction model in estimating VO_2 was tested and compared with the measured VO_2 values, the standard Flex-HR method as well as with other general models (i.e., Rennie et al.'s (2001) and Keytel et al.'s (2005) models). Results indicated no significant difference between observed and estimated Flex-HR parameters and between measured and estimated VO_2 in the overall HR range, and separately in different HR ranges. The ANFIS prediction model (MAE = 3 ml/kg.min) demonstrated better performance than Rennie et al.'s (MAE = 7 ml/kg.min) and Keytel et al.'s (MAE = 6 ml/kg.min) models, and comparable performance with the standard Flex-HR method (MAE = 2.3 ml/kg.min) throughout the HR range. The ANFIS model thus provides practitioners with a practical, cost- and time-efficient method for VO_2 estimation without the need for individual calibration.

The third study presents a new approach based ANFIS for classifying work intensity into four classes (i.e., very light, light, moderate and heavy) by using heart rate monitoring. Intersubject variability (physiological and physical differences) was considered. Twenty-eight participants performed Meyer and Flenghi (1995) step-test and a maximal treadmill test, during which heart rate and oxygen consumption were measured. Results indicated that heart rate monitoring (HR, HR_{max}, and HR_{rest}) and body weight are significant variables for classifying work rate. The ANFIS classifier showed superior sensitivity, specificity, and accuracy compared to current practice using established work rate categories based on percent heart rate reserve (%HRR), with an overall 29.6% difference in classification accuracy between the two methods, and good balance between sensitivity (90.7%, on average) and specificity (95.2%, on average). With its ease of implementation and variable measurement, the ANFIS classifier shows potential for widespread use by practitioners for work rate assessment.

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LIST OF ABBREVIATIONS

%CHRR	Percentage of corrected cardiac reserve
$\%HR_{max}$	Percentage of maximal heart rate
%HRR	Percentage of heart rate reserve
$\%VO_{2max}$	Relative oxygen consumption
$\%VO_{2R}$	Percentage of oxygen consumption reserve
ACGIH	American Conference of Governmental Industrial Hygienists
ACSM	American College of Sports Medicine
ADP	Adenosine Diphosphate
AI	Artificial intelligence
AIHA	American Industrial Hygiene Association
ANFIS	Adaptive neuro-fuzzy inference systems
ANN	Artificial neural networks
ATP	Adenosine Triophosphate
BMI	Body mass index
BR	Breath rate
CO_2	Carbon dioxide
COG	Center of gravity
CV	Coefficient of variation
DIT	Diet induced thermogenesis
dmEFuNN	Dynamic evolving fuzzy neural network
ECG	Electrocardiography
EE	Energy expenditure
FALCON	Fuzzy adaptive learning control network
FIS	Fuzzy inference systems
FL	Fuzzy logic
FQRNT	Fonds Québécois pour la recherche sur la nature et les technologies
GUI	Graphical user interface
HR	Heart rate

HR^{4th}	Heart rate at the fourth minute after the beginning of a rest period
HR_{max}	Maximal heart rate
HR_{rest}	Resting heart rate
HR_{work}	Average heart rate during work
ISO	International Organization for Standardization
LOA	Limits of agreement
MAE	Mean absolute error
MAPE	Mean absolute percentage error
MF	Membership function
MLP	Multilayer perceptron
MPL	Muscle Physiology Laboratory
N_2	Nitrogen
NEFCON	Neuronal fuzzy controller
NEFPROX	Neuro-fuzzy function approximation
NSERC	Natural Science and Engineering Research Council of Canada
O_2	Oxygen
PAR-Q	Pre-activity readiness questionnaire
PC	Phosphocreatine
RMSE	Root mean square error
RPE	Ratings of perceived exertion
SC	Soft computing
SONFIN	Self constructing neural fuzzy inference network
TEE	Total energy expenditure
VO_2	Oxygen consumption
VO_{2max}	Maximal oxygen consumption or aerobic capacity
VO_{2rest}	Resting oxygen consumption
VO_{2work}	Average oxygen consumption during work

LIST OF APPENDICES

CHAPTER 1: INTRODUCTION

1.1 Motivation

The 18th century witnessed a tremendous increase in mechanization and automation in work environments involving muscular work. Machines, computers and robotic technologies have been rapidly evolving in recent years and have replaced or reduced human effort. Nevertheless, still about 20-25% of the working population in industrialized countries are employed in physically demanding occupations (Rutenfranz et al., 1990; Mital et al., 2000). This percentage is much higher in non-industrialized countries.

Nowadays, despite increased mechanization in the workplace, the majority of jobs especially in heavy industry (e.g., coal, steel, oil, construction and forestry) are still physically demanding and can be hazardous (Rayson, 2000; Salvendy, 2001). For instance, it has been shown that silvicultural work activities place moderate to heavy physical demands on workers due to the hard working conditions. Mostly, silvicultural work requires manual labour which includes carrying chainsaws and other tools, felling trees, clearing bush, bending and lifting and other strenuous activities. Moreover, silvicultural workers often need to move over long distances within the forest in order to treat different batches, which may place addition physical strain on workers. Varying weather conditions (e.g., heat, cold, wind and fog) during the winter and the summer represent another challenge for silvicultural workers. As a result, precautions (e.g., safety clothing, safety shoes, helmet, and safety goggles) must be taken by workers to ensure their safety, which may also represent an additional source of physical exertion. In such a work environment, where workers' lives and health might be at risk, the priority is to ensure operational efficiency and workers' safety, which can be achieved through the implementation of work physiology principles.

Studies have shown that excessive workloads and inadequate work-rest schedules are the main cause of physical fatigue which results in decreased productivity and motivation, poor quality of work, inattentiveness, job dissatisfaction, accidents and injuries (Brouha, 1967;

Abdelhamid, 1999). Therefore, ergonomics and occupational health and safety researchers have demonstrated the importance of understanding the physical demands of work which is the first step in designing work and workplaces and selecting workers for a specific task. Studies have shown that designing jobs based on the balance between the physiological capacity of the workforce and the energetic demands of the physical jobs is a key factor in maintaining workforce safety, health, and productivity (Malchaire et al., 1984; Abdelhamid, 1999; Wu and Wang, 2002; Dempsey et al., 2008).

This research was motivated by the need to develop practical means to determine physical demands (energetic cost) associated with work environments requiring muscular effort (i.e., forestry work) and to evaluate whether these physical demands are within the workforce's capability. The developed methods should have practical applications in work environments, especially when large population groups are studied. In this sense, they should be time and cost efficient, based on easily-measured variables, non-invasive, able to handle the uncertainty inherent in the human physiology system and able to handle the nonlinearity associated with physiological response variables.

1.2 Overview of work physiology

There has been much debate about the efficiency of classical work study methods in work assessment involving manual labour. Studies have shown that some of the physiological changes experienced by the worker during physical activities strongly indicate the work intensity (Tomlinson and Manenica, 1977; Rodahl, 1977). Therefore, ergonomists recommended the use of physiological methods instead of classical work study methods for assessing work involving manual effort (Tomlinson and Manenica, 1977). In addition, unlike the classical work study methods, physiological methods consider the capacities of the workforce in work assessment and design. Moreover, physiological methods may provide additional information on other sources of stress exerted on workers such as those caused by various environmental conditions.

The scientific discipline concerned with understanding the metabolic and physiological changes experienced by workers during manual work is called work physiology (Astrand and Rodahl, 1986; Abdelhamid, 1999). The main objective of work physiology is to allow workers to perform work without developing physical fatigue resulting from physiologically demanding work (Astrand and Rodahl, 1986; Abdelhamid, 1999). According to Astrand and Rodahl (1986), the application of work physiology principles depends on two complementary steps: measuring and evaluating physiological demands of work activities that represent the basic steps towards understanding the energetic demands of work. The proper understanding of these demands will allow managers and decision-makers to decide on appropriate administrative and engineering interventions to ultimately improve worker's safety, health and productivity. The advantages of applying principles of work physiology in different types of industries and work environments may include the following, (Abdelhamid, 1999):

- The ability to determine if a specific worker is able to perform a certain job without experiencing physical fatigue.
- The ability to determine if the energetic/physiological demand of a certain job is within the physiological capacities of the workforce.
- The ability to identify the most demanding tasks in order to assign qualified workers to perform them, or make them less demanding to be suitable to the majority of the workforce.
- If the work can be performed by different methods, one can determine the best method to perform the work by comparing the physiological demands associated with each method.
- If the work involves different types of muscular effort (i.e., static and dynamic), then one can separately evaluate each type of muscular effort.
- The ability to develop appropriate work-rest cycles.
- The ability to predict the energetic/physiological demands under different scenarios (e.g., workloads and work layouts).

1.2.1 Measuring physiological demands of work activities

Typically, the physiological demand of work (absolute workload) is determined by measuring worker's energy expenditure (EE) or oxygen consumption (VO_2) during the work. It is well documented in the literature that VO_2 reflects EE and absolute physical workload associated with physically demanding jobs (Malchaire et al., 1984; Smolander et al., 2008; Wu and Wang, 2002; Bouchard and Trudeau, 2008).

Exact techniques, which use direct measurement of VO_2, are costly, time consuming, invasive and may require sophisticated equipment and therefore often impractical for field and large scale studies (Valanou et al., 2006; Firstbeat Technologies Ltd., 2007). Therefore, attempts have been made to find alternative feasible methods for VO_2 estimation. Researchers have thoroughly investigated the relationship between oxygen consumption and heart rate (HR), since the latter can be easily and non-invasively measured. Studies have shown that HR monitoring provides a feasible technique for estimating VO_2 in field studies based on individual's VO_2-HR relationship, which is called individual calibration process (Wareham et al., 1997, 1998; Bassett, 2000; Rennie et al., 2001; Garet et al., 2005). This calibration process involves measuring HR and VO_2 for an individual performing a graded exercise, typically on a treadmill, a stationary bicycle, or a step-test. Regression analysis is applied to obtain the relationship between the measured HR and VO_2. Once this relationship is established, an estimate of VO_2 can be calculated using the HR data collected in the field for each individual.

Different types of VO_2-HR relationships have been investigated and proposed, such as linear (Schulz et al., 1989; Bouchard and Trudeau, 2008), exponential (Li et al., 1993; Bitar et al., 1996), logarithmic (Schultz et al., 1989), 2nd order (Schultz et al., 1989; Bitar et al., 1996; Davidson et al., 1997) and 3rd order (Bitar et al., 1996) polynomial relationships and the Flex-HR method (Spurr et al., 1988; Ceesay et al., 1989; Schultz et al., 1989; Livingstone et al., 1990; Van den Berg-Emons et al., 1995, 1996; Fogelholm et al., 1998). The linear calibration and the Flex-HR methods are the most widely used methods for VO_2 estimation in field studies (Garet et al., 2005; Smolander et al., 2008).

The linear calibration method assumes a linear relationship between VO_2 and HR for a wide variety of activities (Wyndham et al., 1962; Poulsen and Asmussen, 1962; McArdle et al., 1971; Rodahl et al., 1974; Evans et al., 1983; Gordon et al., 1983; Astrand and Rodahl, 1986). Due to its simplicity, the linear calibration method has become the traditional way to use HR for VO_2 estimation in work physiology (Smolander et al., 2008). On the other hand, the Flex-HR method assumes a linear relationship between HR and VO_2 above a transition point (Flex point) and a more variable relationship (which uses the average of a series of HR values during rest) below this point (Garet et al., 2005; Valanou et al., 2006). The Flex point is empirically defined as the average of the lowest HR during exercise and the highest HR during rest (Valanou et al., 2006). Therefore, the Flex-HR method is based on four parameters, namely the resting energy expenditure or oxygen consumption (VO_{2rest}), the Flex point, the slope and the intercept of the linear line describing the VO_2-HR relationship above the Flex point.

1.2.2 Evaluating the physiological demands of work activities

The second important step towards understanding the energetic demands of work is to evaluate the physiological demands of the work activities. This step determines whether the energetic demands of the activities are excessive such that workers might face the risk of undue physical fatigue (Abdelhamid and Everett, 2002). This step is achieved by matching the workload or workers' energy expenditure during work activities (i.e., VO_2) with their physiological capabilities to perform the activities (VO_{2max}), which results in a ratio known as relative workload. VO_{2max} (also called maximal oxygen consumption or aerobic capacity) represents the maximum capacity of individuals to consume oxygen during physical activities, which indicates the cardiorespiratory or physical fitness of individuals. Nowadays, classification of work rate based on published limits and guidelines is the most common way to evaluate the physiological demands of work activities (Abdelhamid and Everett, 2002).

There are three main methods for classifying work rate. In the first method, work rate is classified using norms and limits based on energy expenditure or oxygen consumption. It is well established that for every litre of oxygen consumed approximately 4.83 kcal of energy are produced (Grandjean, 1980; Abdelhamid, 1999). Christensen (1964) and Astrand and Rodahl (1986) proposed limits and norms of oxygen consumption to classify work rate. In addition, the American Industrial Hygiene Association (AIHA, 1971) proposed norms of minute energy consumption to assess workload and classify work rate. Other studies proposed norms of energy consumption based on 8-hour workdays such as Hettinger (1970) and AIHA (1971). In the second method, work rate is classified based on variables that have a linear relationship with energy consumption, such as HR (Grandjean, 1980). Using HR to assess workload and classify work rate is considered one of the most practical and useful methods for workload assessment since HR can be easily measured (Grandjean, 1980). The third method is related to a more recent study conducted by the U.S. Department of Health and Human Services (1996) that recommends the use of relative oxygen consumption ($\%VO_{2max}$) for classifying work rate. This classification method provides an accurate means for workload evaluation and therefore it is considered as the gold standard for classifying work rate (U.S. Department of Health and Human Services, 1996; Haskell and Pollock, 1996; Pollock et al., 1998). For practical applications, several studies recommended the use of a percentage of the difference between maximal heart rate (HR_{max}) and resting heart rate (HR_{rest}), known as percentage of heart rate reserve (%HRR), for work rate classification (Haskell and Pollock, 1996; Pollock et al., 1998; American College of Sports Medicine (ACSM), 2006). The estimation of HR_{max} has been widely computed as: 220-age (Fox et al., 1971; Londeree and Moeschberger, 1982; Astrand and Rodahl, 1986; Tanaka et al., 2001; Robergs and Landwehr, 2002; McArdle et al., 2010).

1.2.3 Contribution of work physiology to forest industry

Forestry work is globally considered one of the physically demanding work environments that involve a large amount of manual work (Smith and Sirois, 1982; Scott and Christie, 2004; Rodio et al., 2007). Studies have shown that the increasing injury rate in forestry work is mainly attributable to excessive physiological and biomechanical demands placed on the workers, which affect both the cardiovascular and musculoskeletal systems (Scott and Christie, 2004). In addition to the extreme physical and physiological loads required by the work, there are other factors that place additional stress on the workers. These factors include: working under extreme climatic conditions, working on steep or uneven terrains, walking for long distances to reach the treated field, and working on terrain with fallen trees that create obstacles (Scott and Christie, 2004; Rodio et al., 2007).

In light of the previous discussion, work physiology may play an important role in maintaining forestry workers' safety and productivity due to the following reasons. Forestry work involves a large number of tasks with moderate to heavy intensity (Smith and Sirois, 1982; Sirois and Smith, 1985). Furthermore, in forestry work, the fitness level of workers is often less than optimal and the work environment is physically stressful (Smith and Sirois, 1982; Scott and Christie, 2004; Rodio et al., 2007). In addition, in order for the decision-makers to effectively design forestry work and assign jobs, physiological demands of forestry work activities must be known in advance (Smith and Sirois, 1982). Therefore, the implementation of work physiology principles in forestry work allows the effective design of work methods, workers selection, the effective design of work-rest cycles, and the determination of assigned workloads with the ultimate goal of ensuring operational efficiency and workers' safety (Smith and Sirois, 1982; Rayson, 2000).

The application of work physiology in forestry work environments faces many challenges related to the selection of the physiological response variables, the equipment and procedures used for data collection. According to Sirois and Smith (1985), some of the challenges may include the following:

- The selected physiological response variables must reflect both the stress placed on the worker due to the work intensity as well as the thermal environmental stress.

- The selected physiological response variables must be easily and non-invasively measured in workplaces.
- The data collection equipment must not interfere with the task requirements (e.g., suitable during static and dynamic work activities).
- The data collection equipment must be cost-efficient.
- The data collection procedure must be time-efficient.
- The data collection procedure must be non-intrusive.

1.3 Dissertation statement

Ergonomists and work physiology researchers have emphasized the importance of understanding (i.e., measuring and evaluating) the physiological demands of work activities in order to maintain workers' safety, health and productivity. Exact techniques to measure and evaluate the physiological demands of work activities are costly, time consuming, and require sophisticated equipment and therefore are impractical in large-population field studies (Valanou et al., 2006; Firstbeat Technologies Ltd., 2007). Therefore, attempts have been made to find alternative estimation methods of absolute (VO_2) and relative ($\%VO_{2max}$) workloads.

The current practice to estimate VO_2 is based on an individual calibration process by which individual's VO_2-HR relationship is established. Despite the fact that the linear calibration and the Flex-HR methods are widely used for VO_2 estimation in field studies, they have been criticized from several perspectives. The main criticism was the fact that both methods require an individual calibration process to establish an individual's VO_2-HR relationship, which is relatively costly and time consuming, and may require the presence of a trained professional, and therefore impractical in work environments especially with large populations. Another criticism was related to the fact that at low activity levels (lower HR values) the relationship between HR and VO_2 is nonlinear and therefore often deviates from the linear calibration curve yielding inaccurate estimates of VO_2 (Abdelhamid, 1999; Bouchard and Trudeau, 2008; Smolander et al., 2008). Although the Flex-HR method attempted to handle the nonlinearity problem associated with the linear calibration method, it was criticized for the difficulty in determining the Flex point, which depends on several factors, such as the physical and physiological characteristics of the population under study, the type and number of the physical activities (Garet et al., 2005). All these variables may cause uncertainty in determining the Flex-HR parameters. Another problem is related to the fact that most of the previous modeling efforts were made based on linear prediction models using regression analysis which, although easy and simple to apply, has several limitations such as the requirement of a large sample size and the inability of capturing nonlinearity, uncertainty and true relationship between physiological variables in the human physiological system (Shimizu and Jindo, 1995; Park and Han, 2004).

On the other hand, the current practice of evaluating the physiological demands of work activities is to classify the work rate based on its intensity (e.g., very light, light, moderate and heavy). Since exact techniques to determine relative workload (i.e., $\%VO_{2max}$) are impractical for large population and field studies (i.e., costly, time consuming, requires sophisticated equipment), researchers proposed the use of %HRR to estimate $\%VO_{2max}$ for work classification. Although the %HRR classification method is simple to apply in work environments, it has been criticized from several perspectives. The main criticism was the fact that the %HRR method depends only on HR monitoring variables which do not account for the high inter-variability between individuals and therefore results in inaccurate estimation of relative workload and poor work classification (Melanson and Freedson, 1996; Valanou et al., 2006).

Therefore, there is a need to develop practical means to estimate the absolute (VO_2) and relative ($\%VO_{2max}$) workloads in order to better quantify and evaluate the physiological demands of work activities. This research will provide practical means to measure and evaluate the physiological demands of work activities using the concepts of fuzzy logic and fuzzy set theory. In this research, we focus on silviculture work activities performed in various forests in the Province of Québec since forestry work is considered physically demanding and therefore it represents a potential environment to apply work physiology principles.

1.4 Dissertation objectives

The main objectives of this dissertation are to:

1. Develop a practical method to estimate oxygen consumption/energy expenditure at workplaces without the need for individual calibration using heart rate measurements. The developed method should take the aforementioned limitations of the traditional linear calibration method into consideration.
2. Develop a practical method to estimate individual's VO_2-HR relationship using easily measured variables, without the need to perform any graded exercise tests and hence estimate individual's oxygen consumption/energy expenditure during work. The developed method should take the aforementioned limitations of the Flex-HR method into consideration.

3. Develop a practical method for estimating relative workloads and classifying work rate using easily measured variables at workplaces.
4. Compare the developed methods with current practices from the literature and actual field measurements.

1.5 Research methods

Human physiological systems are complex systems characterized by nonlinearity, uncertainty, and unknown relationships between variables. For these reasons, conventional methods of energy expenditure estimation (i.e., based on regression analysis) may be inadequate methods for such systems (Shimizu and Jindo, 1995; Park and Han, 2004). Alternatively, machine learning techniques, such as Bayesian networks, artificial neural networks (ANN), fuzzy inference systems (FIS), and adaptive neuro-fuzzy inference systems (ANFIS) are becoming increasingly more useful because they have the ability to deal with complex systems such as these. As well, they produce consistently accurate results, despite a relatively small sample size (Chang et al., 2013).

Bayesian networks are type of soft computing techniques that are widely used for pattern classification and function approximation. Bayesian networks constitute a powerful method of probabilistic (distribution-based) representation that require prior probabilities to quantify the uncertainty involved in the occurrence of events (Othman and Yau, 2007; Azizi et al., 2012). Certain advantages of Bayesian networks include: the fact that they are based on well established probability theories (Schott, 2005), the ability to learn the structure of a system and the relationships between variables (Uusitalo, 2007), the ability to incorporate new knowledge (McCloskey, 2000; Ticehurst et al., 2008), the ability to handle a lack in information and relatively small sample sizes (Uusitalo, 2007; Kragt, 2009). In addition to these, they are able to reason in two different directions (forward and backward) (McCloskey, 2000), and able to provide a visual decision support tool (McCloskey, 2000; Kragt, 2009). On the other hand, there are several significant drawbacks associated with the Bayesian networks. One particularly significant setback is that Bayesian networks require the states in the model to be known (Schott, 2005). In addition, Bayesian networks can learn only the causal patterns that are identified by the designer (McCloskey, 2000). Other disadvantages may include difficulties related to the design of the Bayesian network, difficulty in expressing expert knowledge in the form of accurate probability distribution, difficulty in convincing experts to universally agree on the structure of the model, limitations of the Bayesian network software packages to adequately deal with continuous data, as well as the Bayesian networks' inability to include feedback effects (Uusitalo, 2007; Barton et al., 2008; Kragt, 2009). In order to derive expert knowledge and make statements about the distributions of the variables used in Bayesian networks, experts need to agree on the functionality of the nodes within the network, the state of these nodes, and their relational interactions within the network itself (Pollino, 2008).

ANN consists of individual models of the biological neurons that are interconnected in a form of a network (Ben Ghalia and Alouani, 1995). One of the main strengths of ANN is their structure, which allows for parallel information processing and therefore results in high-speed computations (Rumelhart and McClelland, 1987; Lippmann, 1987; Ben Ghalia and Alouani, 1995). Another advantage of ANN is its inherent ability to learn and self-organize in a way that allows it to adapt to environmental variations and discrepancies and to learn complex input characteristics (Poggio and Girsi, 1990; Ben Ghalia and Alouani, 1995). Of particular note is ANN's ability to learn complex nonlinear input-output mapping. This has made ANN a powerful tool for nonlinear function approximation and pattern classification (Cybenko, 1989; Hornik et al., 1989; Narendra and Parthasarathy, 1990; George and Cardullo, 1999). Nevertheless, due to the complex structure of ANN, the mapping rules are invisible and difficult to understand, which makes ANN a black box (Vieira et al., 2003; Ben Ghalia and Alouani, 1995). Another disadvantage of ANN is that it does not make use of human expertise in its learning process (Vieira et al., 2003).

On the other hand, in contrast to ANN, FIS has the ability to approximate human reasoning capabilities and thereby develop an inference mechanism based on IF-THEN rules from knowledge-based systems (input-output data or human expertise) (Zadeh, 1973; Ben Ghalia and Alouani, 1995). Therefore, FIS proves itself to be a strong mathematical tool with an intrinsic ability to handle the inevitable uncertainties associated with human cognition processes (Ben Ghalia and Alouani, 1995). In addition, FIS has demonstrated an efficacy to approximate nonlinear functions and pattern classification with adequate proficiency (Kosko, 1992; Wang and Mendel, 1992; Alshaban and Ali, 2010). Unlike ANN, FIS consists of rules that are visible, structured, easy to understand and interpret, and can include numerical as well as linguistic knowledge (Ben Ghalia and Alouani, 1995). However, despite these seemingly strong advantages, FIS lacks the ability to learn and adapt to environments in order to produce output within the required error rate, which is the main advantage of ANN (Vieira et al., 2003). A comparison between ANN and fuzzy systems for classifying ECG signals was conducted in Alshaban and Ali (2010). The study showed that fuzzy systems require less time to classify ECG signals and that fuzzy systems render methods of analysis less problematic than ANN. As well, fuzzy systems can incorporate new cases by adding an additional fuzzy rule as required, whereas ANN requires each new case to be added to the input set and the network to be trained for each new case.

ANFIS is a hybrid system that combines the two methods (ANN and FIS). It can be described as a fuzzy inference system put in a framework of an adaptive network to optimize the FIS parameters. ANFIS possesses the strengths of both FIS (e.g., humanlike thinking and reasoning through IF-THEN rules, and ability to incorporate expert knowledge available in linguistic form) and ANN (e.g., learning and optimization abilities, and connectionist structure) (Al-Saud, 2012). Not only are the advantages of FIS and ANN combined to create a potential for better accuracy as a comprehensive system, ANFIS eliminates or reduces certain drawbacks associated with both methods. For instance, it has been shown that ANFIS reduces the need for an expert (Tsoukalas and Uhrig, 1997). ANFIS is a powerful tool to construct complex and nonlinear relationships between input-output data for function approximation and pattern classification (Miraftab and Mansour, 2006; Ubeyli and Guler, 2006; Turkmen et al., 2009; Yildiz et al., 2009). It possesses the ability to incorporate numerical and linguistic knowledge into the IF-THEN rules, and therefore has the ability to learn from both input-output data as well as from expert knowledge (Turkmen et al., 2009). Other advantages of ANFIS include, its fast learning and adaptation capabilities (Turkmen et al., 2009), its ease of implementation and interpretation (Hines and Wrest, 1997), model compactness and the resulting ability of ANFIS to learn from a small data set (Asthana and Kumari, 2013), the ability to automatically tune FIS parameters (Turkmen et al., 2009; Asthana and Kumari, 2013), proven accuracy without complicated mathematical functions, and the availability of software packages to easily use and develop ANFIS. However, similar to all machine learning techniques, there are some drawbacks associated with ANFIS. One of the principal disadvantages is what is known as the “curse of dimensionality”, which refers to the impact of an increased number of inputs on the complexity level of ANFIS (increased number of rules) (Hines and Wrest, 1997). Also, there is no universal method to determine the type of membership functions associated with input variables, which may influence the behaviour of ANFIS (Giovanis, 2012). In addition to these attribute, developing an accurate ANFIS model relies heavily on the accuracy and effective representation of training data (Hines and Wrest, 1997). Moreover, there are additional setbacks associated with the back-propagation gradient descent method, such as slow convergence with increased input variables and the fact that it may not be able to find the optimum solution or global minimum of the objective function (even though it does produce a solution close to the global minimum) (Rumelhart et al. 1986; Mitchell, 1996; Giovanis, 2012).

In light of the advantages and disadvantages mentioned here, there is no clearly defined 'good' or 'bad' machine learning technique. An efficient technique may be chosen depending on the research goals and data sets. In the present research, we have chosen ANFIS as a tool to estimate and evaluate the physiological demands of work from heart rate measurements. In addition to the general advantages of ANFIS referred to above, the following are more specific reasons for selecting ANFIS specifically for the present research. This research is concerned with measuring and evaluating physiological demands of different work activities. This requires adequate physiological and biological data collection. Since this particular type of data often exhibit *a priori* unknown statistical properties, it is more suitable for this research, to use methods that are based on learning, rather than using non-adaptive methods (e.g., Bayes classifier) (Lorenz et al., 1997). As well, this research deals with the human physiological system and actual work environments, where knowledge is uncertain, ambiguous, or imprecise. Thus, ANFIS is more appropriate for use under such conditions, especially since it has the ability to represent certain elements as members of different sets with different degrees of membership (Hamdan, 2013). In addition, ANFIS has the ability to incorporate *a priori* knowledge in the rule-base of the model, and therefore it may allow the designer to incorporate the experience of physiologists and doctors in the rule-base (Lorenz et al., 1997). Another reason to select ANFIS is its practicality. Since all fuzzy rules can be programmed in Excel, researchers and practitioners can easily create and apply it in the field as a decision support tool without requiring special equipment or software. It also benefits from the accuracy and simplicity in that it offers transparency in explaining the input-output relationships, which in turn, allows workers and practitioners to better understand the physiological demands of work without requiring costly and hard-to-find technical expertise (Dom et al., 2012; Hamdan, 2013). The structure of ANFIS may also allow for real-time implementation, which might have a great impact on maintaining workers' safety and productivity.

It is also noteworthy that there are different types of membership functions associated with fuzzy systems, such as the singleton, triangular, trapezoidal, and Gaussian types of membership. The selection of membership functions is subjective and often depends on the application requirements. For example, it is common to use a Gaussian membership function if the developed fuzzy model is to be optimized using gradient-descent methods, whereas a triangular or a trapezoidal membership function is intended for use if the fuzzy model is developed based on knowledge obtained from experts (Berthold, 1999). In this research, Gaussian membership functions were used because they are characterized by useful mathematical properties, such as continuity and differentiability, which were required as a result of membership functions that require automatic optimization during the training stage. Another reason for using a Gaussian membership function is that the fuzzy models used in this specific research were developed objectively (based on input-output data) and did not rely on expert knowledge modeling. Moreover, Gaussian membership functions are less sensitive (when compared to Singleton membership functions) to small changes in input variables, and therefore, they reduce the effect of noise in the input variables to account for better accuracy and efficiency (Nafisi et al., 2011).

1.6 Dissertation guide

This dissertation includes seven chapters including this one (Chapter 1), which provides a general introduction. The dissertation will be organized as follows: Chapter 2 presents a background on applied work physiology and its main principles. The chapter discusses the mechanism of energy expenditure in humans during muscular work and the sources of energy required for muscular work. In addition, the main techniques to assess energy expenditure in humans are presented. In particular, different techniques that estimate oxygen consumption/energy expenditure based on heart rate are summarized.

Chapter 3 presents a background on soft computing and its main paradigms. The chapter discusses the concepts of fuzzy logic and fuzzy set theory with special focus on fuzzy systems and their use in objective modeling. In particular, fuzzy inference systems and their main components are discussed in detail. In addition to fuzzy systems, the concept of artificial neural networks is presented. Neural networks' structure and learning algorithm with focus on feed-forward neural networks and supervised learning are also discussed. Finally, neuro-fuzzy systems and their main types are presented. The chapter focuses on adaptive neuro-fuzzy inference systems (ANFIS) as they are mainly used in this dissertation. The structure and learning algorithm associated with ANFIS are also discussed in this chapter.

Chapter 4 (first paper) presents new approaches based on ANFIS for the estimation of oxygen consumption/energy expenditure from heart rate measurements. This chapter comprises two stages in which 35 individuals participated. In the first stage, two individual models are proposed based on ANFIS and analytical methods. In the second stage, a General ANFIS model, which does not require individual calibration, is proposed. The proposed models are compared with current practices for oxygen consumption estimation (i.e., individual calibration and Flex-HR). The chapter concludes by validating the three proposed models with laboratory data and with data obtained from silvicultural workers during their actual work.

Chapter 5 (second paper) presents a new approach based on ANFIS to predict individual's VO_2-HR relationship without the need to perform any graded exercise. The proposed ANFIS prediction model consists of three ANFIS modules for estimating the Flex-HR parameters. The chapter discusses the steps to develop each ANFIS module, which include input variable selection and model assessment using the combination of three-way data split and cross-validation techniques. The chapter concludes by testing the proposed ANFIS prediction model with data obtained from silvicultural workers during their actual work.

Chapter 6 (third paper) presents a new approach based on ANFIS for classifying work rate into four classes, namely very light, light, moderate and heavy, by using heart rate monitoring. The chapter discusses the three main stages for the proposed ANFIS classifier development. In the first stage, significant physiological/physical variables were selected and incorporated into the classifier development. The second stage was concerned with developing the ANFIS classifier from selected input variables. The chapter concludes with the third stage, which is concerned with validating the developed ANFIS classifier using independent test data obtained from silvicultural workers during their actual work. Chapter 7 includes conclusions of the dissertation and future directions of the research. The chapter also summarizes the main contribution of the dissertation to knowledge and industry.

Appendix A describes the steps to develop individual ANFIS models proposed in Chapter 4. Appendix B includes the MATLAB code that was used for the development of the General

ANFIS model proposed in Chapter 4. Appendices C and D include a description (i.e., fuzzy rules, membership functions) of the General ANFIS model developed in Chapter 4 using the training data set and data set from all participants, respectively. Appendix E describes the implementation of the General ANFIS model using Excel. Appendix F summarizes the simultaneous implementation of backward selection method and 10-fold cross validation. Appendix G describes the developed ANFIS prediction model proposed in Chapter 5. It includes a description of the fuzzy rule-base and membership functions of each ANFIS modules (module 1, module 2, and module 3). Appendix H summarizes the implementation of the ANFIS prediction model using Excel. Appendices I and J describe the development of fuzzy IF-THEN rules and backward selection method used in Chapter 6, respectively. Appendices K and L include a description of the ANFIS classifier developed in Chapter 6 and its implementation using Excel, respectively.

CHAPTER 2: BACKGROUND AND LITERATURE REVIEW OF WORK PHYSIOLOGY

2.1 Energy expenditure in humans

Humans require energy for a variety of needs: growing, such as producing and repairing tissues, maintaining bodily functions, such as breathing and respiration, and physical exertion (Institute of Nutrition and Health ROWETT, 2008). One of the primary characteristics of the human body is its ability to perform physical activities at varying intensities and durations, an ability requiring a sufficient amount of energy in order to function properly. Energy is typically obtained by processing nutrients through a series of chemical reactions within various cells in the body (Abdelhamid, 1999). The process encompassing energy intake, storage and expenditure is collectively referred to as the metabolism (Herman, 2007). Figure 2-1 illustrates the process of energy production within the body. According to Grandjean (1980), the metabolic process begins with the continuous breaking down of foodstuffs within the intestines so as to facilitate absorption into the bloodstream. From there, the blood carries most of the nutrients to the liver, where they are stored as an energy reserve that can be called upon whenever the body requires energy to perform physical activities. A small portion of the nutrients is diverted towards fueling various bodily functions.

According to Institute of Nutrition and Health ROWETT (2008), the total energy expenditure (TEE) is the total amount of energy that a human uses to function in a day, comprising of three components.The first component concerns the energy requirements during physiological and mental rest, which is known as the basal metabolic rate. The basal metabolic rate, or BMR, represents approximately either 60 % or 40% of the TEE, depending on whether the individual is active or not. The second component concerns the energy requirements for the digestion, absorption and transportation of food components within the human body, a process called diet induced thermogenesis, or DIT. DIT represents approximately 10 % of the TEE for both active and inactive individuals. The third component is concerned with the energy required for physical exertion. The most variable component of the three, the third component depends on several factors: duration and intensity of activity, body mass and physical fitness. The third component represents approximately 30% and 50% of TEE for active and inactive individuals respectively (Institute of Nutrition and Health ROWETT, 2008). The third component is also the primary component used in the context of this dissertation, a component referred to as energy expenditure or EE. The following subsections describe in detail the mechanisms for energy flow within the human body. Included is a discussion pertaining to one of the most important systems in the human body that is related to body movement, sources of energy and energy expenditure relating to muscular exertion.

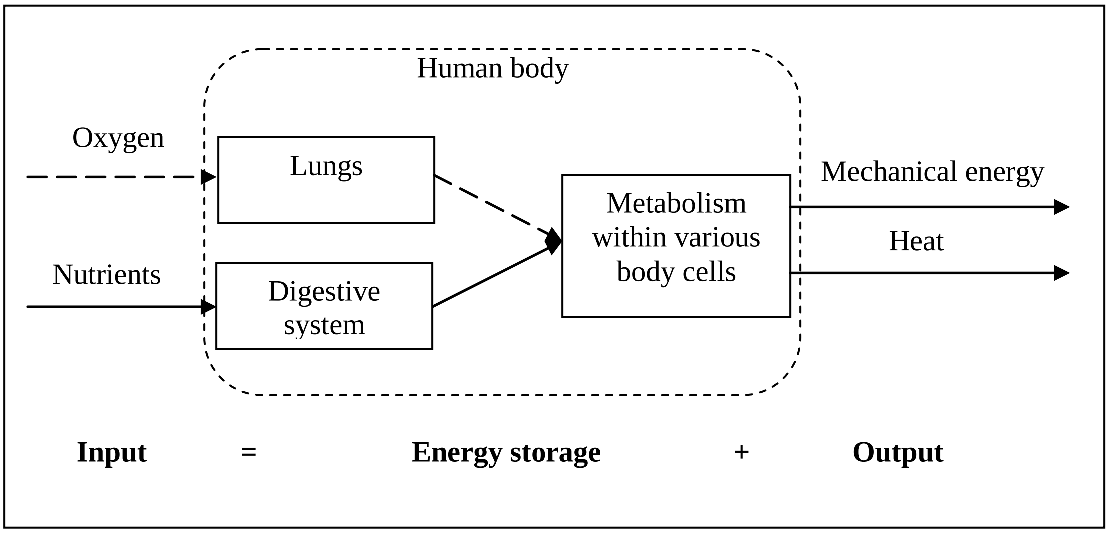

Figure 2-1: Energy production in the human body; adapted from Grandjean (1980)

2.1.1 Muscular system

A muscular system is one of several musculoskeletal sub-systems that allow for body movement. Approximately 40% of body weight is accounted for by muscles through which body movement is possible (Grandjean, 1980). The muscle fibre constitutes the structural unit of the muscle so that each muscle is composed of fibres, numbering typically between 100,000 and 1,000,000 and of various lengths dependent on the size of the muscle (Grandjean, 1980). These muscle fibres are bound together by connective tissues, forming the entire muscle itself (Karpovich and Sinning, 1971).

Muscular contraction is the most important property of the muscular system, one through which force is generated. According to the Muscle Physiology Laboratory MPL (2000), there are four types of muscular contractions through which various forces are generated. The first type of muscular contraction is the concentric contraction, allowing for the muscle to shrink in order to produce the required force to lift a load. An example of a concentric contraction would be lifting a dumbbell with a bicep curl. The second type of muscular contraction is called an eccentric contraction, whereby force is generated through the lengthening of the muscle. An example of an eccentric contraction would be performing a push-up. The third type of muscular contraction is called the isometric contraction, where force is generated while the muscle is flexed for a period of time. An example of a isometric contraction would be holding a weight in a fixed position for a period of time (Muscle Physiology Laboratory MPL, 2000). The fourth type of muscular contraction is the passive contraction (stretch), which involves muscle lengthening while in a passive state (non-contracting state). An example of a passive contraction would be the feeling one may experience when attempting to touch one's toes while standing upright (Muscle Physiology Laboratory MPL, 2000).

2.1.2 Energy sources for muscles

The chemical composition of a muscle comprises of proteins, carbohydrates, fats, nitrogenous extractives, non-nitrogenous extractives, pigments, enzymes and inorganic salts (Karpovich and Sinning, 1971). Proteins, such as actin and myosin, play a particularly important role in muscular contraction. Chemical reactions occurring in the muscle produce energy that acts upon the actin and myosin allowing the muscle to contract (Grandjean, 1980). Muscular contractions are essentially the transformations of chemical energy into mechanical energy occurring within the muscle.

In all cells, including muscle cells, carbohydrates, fats and proteins combine to form a high-energy phosphate compound known as adenosine triophosphate, or ATP, which is considered the primary source of energy for virtually all muscular contractions (Karpovich and Sinning, 1971). The energy for muscular contractions is derived from the chemical breakdown of ATP into a low-energy state known as adenosine diphosphate, or ADP, and inorganic phosphate. The amount of ATP available for immediate use is typically limited as it cannot be stored in the body; accordingly, it needs to be synthesized by the body on a continuous basis. The immediate resynthesis of ATP is based on the breakdown of phosphocreatine, or PC, which then combines with ADP to form ATP. However, as PC itself is also limited in the body, another source of energy is required to continually fuel the ATP resynthesis cycle. The compound is called glycolysis, which results from the breakdown of glycogen, a form of sugar obtained from carbohydrates and proteins, into pyruvic acid and then, if oxygen is not used, into lactic acid

(Karpovich and Sinning, 1971). Lactic acid was always considered as a metabolic waste that caused fatigue and muscle soreness. Not too long ago, it has been found that lactic acid plays an important role in generating energy during exercise (Brooks et al., 2006). Nevertheless, the accumulation of lactic acid in the blood stream may cause fatigue. The phase of energy production described above is referred to as the anaerobic phase, as oxygen is not utilized. The anaerobic reaction is considered a source of immediate and short-lasting energy, allowing for the performing of heavy physical activity for a short duration of time, such as sprinting for a short period of time (Abdelhamid, 1999).

When oxygen is required to sustain muscle contractions for an extended period of time, the phase of energy production is referred to as the aerobic phase. The energy production during the aerobic phase includes the breakdown of muscle glycogen primarily into pyruvic acid, which then undergoes a chemical process known as the Krebs cycle (Karpovich and Sinning, 1971). During the Krebs cycle, pyruvic acid is further broken down via oxidation, resulting from continuous oxygen consumption, to yield water and carbon dioxide (Grandjean, 1980). The process produces enough energy to resynthesize a large quantity of PC and ATP. The energy produced by the aerobic phase is approximately 18 times that of the energy produced by the anaerobic phase (Karpovich and Sinning, 1971). Consequently, the aerobic reaction produces energy allowing one to perform moderate physical activity for long periods of time (Abdelhamid, 1999). It is worth mentioning that both energy production phases may overlap to produce energy, of which approximately 34% is utilized for physical exertion with the remainder being dissipated as heat (McArdle et al., 2010).

2.1.3 Types of physical work

In light of the previous discussion, physical work that requires muscular effort can be divided into two types: dynamic work and static work. In dynamic work, the muscles are capable of a rhythmic contraction and extension, such as in bicycle pedaling. Such a rhythmic cycle allows for continuous blood flow to the muscles (during extension) to supply the muscles with energy-rich sugar and oxygen as well as from the muscles (during contraction) to remove the waste (Grandjean, 1980). In static work, the muscles stay in a contracted state for a prolonged period of time, such as when carrying a weight (Grandjean, 1980; Abdelhamid, 1999). During static work, the contracted muscle applies pressure to blood vessels restricting the blood flow through the muscle. This restriction depends on the level of muscle contraction. To illustrate, blood flow through the muscles at maximum or near maximum contraction is impossible, while blood flow will be less restricted at lower contraction levels. As a result, no additional sugar or oxygen is allowed into the muscle and waste products accumulate instead. The effect of this waste product accumulation manifests itself in the form of physical fatigue when performing heavy static work for extended periods of time. Several studies have found that under similar situations, static work requires more oxygen, longer periods of rest and a higher heart rate than dynamic work (Malhotra and Sengupta, 1965; Hettinger, 1970; Grandjean, 1980).

2.2 Assessing physiological demands of physical activities

Energy expenditure can be expressed in calories, abbreviated as cal, or joules, abbreviated as J. Cal is defined as the energy required to increase the temperature of 1 gram of water from 14.5 degrees centigrade to 15.5 degrees centigrade. A joule, or J, is defined as the energy required to move 1 kilogram of weight a distance of 1 meter with 1 Newton of force (Institute of Nutrition and Health ROWETT, 2008). In the context of this dissertation, kilocalories, or kcal, will be used as a unit for measuring EE. One kcal is equal to 1,000 cal or 4.184 kilojoules, or kJ. In general, energy expenditure can be assessed by either exact methods or by estimation methods. The exact methods include three techniques: direct calorimetry, indirect calorimetry and non-calorimetric methods. EE can be estimated by rather simplistic means, such as heart rate monitoring.

2.2.1 Exact methods for assessing energy expenditure

2.2.1.1 Direct calorimetry

Calorimetry is the process of measuring the amount of energy expended by using a device known as a calorimeter. Direct calorimetry is based on the fact that metabolic processes occurring in mammals are always accompanied by heat dissipation, a form of energy that can be discreetly measured (Goran and Treuth, 2001; Abdelhamid, 1999). In direct calorimetry, the EE of an individual over a given period of time is quantified by directly measuring the amount of heat dissipated from the body during that time frame (Valanou et al., 2006).

The first calorimeter, called an ice calorimeter, was developed in the early 1780s by Antoine Lavoisier and Pierre-Simon Laplace (Chaires, 2008). Lavoisier’s ice calorimeter comprised of two chambers; one chamber, the inner chamber, was inside of the outer chamber, insulated by a layer of ice (Miller, 2005). In Lavoisier’s first experiment, a guinea pig was used to measure its EE. The guinea pig was placed inside of the inner chamber so that the heat it produced caused the ice surrounding the inner chamber to melt. The resulting loss in volume as measured by the melting water was used to determine the amount of heat dissipated by the animal (Durnin and Passmore, 1967; Kleiber, 1975; Brooks et al., 1995; Miller, 2005; Johnston, 2006). The first attempt for human EE measurement was made in 1903 by Atwater and Benedict using a respiration calorimeter (Kleiber, 1975; Johnston, 2006).

Currently, the direct calorimetry process has evolved to include a room-sized chamber called the calorimetry chamber or calorimeter (Miller, 2005; Valanou et al., 2006). A participant considered for the EE measurement stays in the calorimety chamber for 24 hours to measure heat lost from his/her body during rest or different activities (Consolazio et al., 1963; Miller, 2005). The calorimetry chamber includes pipes that allow water to circulate both in and out of the pipes. Heat lost from the body is in two forms: evaporative and non-evaporative. Measuring the evaporative heat lost depends on the degree of change in the moisture content of the air in the calorimetry chamber (Miller, 2005), whereas measuring the non-evaporative heat lost depends on the temperature of the ingoing and outgoing water as well as the amount of water flow during different intervals of time (Montoye et al., 1996; Miller, 2005; Valanou et al., 2006).

Direct calorimetry is extremely accurate method for EE measurement with less than 1% estimation error (Johnston, 2006; Valanou et al., 2006). However, it is highly invasive, unsuitable for certain activities, and highly costly because it requires specialized equipment, laboratory settings and skilled technicians (Abdelhamid, 1999; Miller, 2005). Although the limitations mentioned above restrict its use in academic research, especially in practical and large population studies, direct calorimetry is often used as a standard method to validate the accuracy of other proposed methods for EE measurements (Abdelhamid, 1999; Johnston, 2006).

2.2.1.2 Indirect calorimetry

Due to the restrictive nature of direct calorimetry, scientists attempted to determine an individual's EE through a proxy instead of directly measuring heat production, and therefore this approach is called "indirect calorimetry". One of the most important and commonly used proxies is the rate of respiratory gas exchange during the biological reactions in the body. Indirect calorimetry is based on the fact that all energy-releasing reactions in the body depend on the food oxidization process that is accompanied by oxygen consumption and carbon dioxide production (McArdle et al., 2010). Therefore, in indirect calorimetry, an individual's EE is estimated using the amount of oxygen consumed (i.e., VO_2) and carbon dioxide produced (Simonson and DeFronzo, 1990; Brooks et al., 1995; Ainslie et al., 2003; McArdle et al., 2010). In general, the indirect calorimetry approach provides a relatively inexpensive, acceptably accurate and less invasive means for determining individual's EE when compared to the direct calorimetry approach (Abdelhamid, 1999). According to Levine (2005), there are four main techniques for measuring the VO_2 using indirect calorimetry: closed-circuit systems, confinement systems, total collection systems and open-circuit indirect calorimetry systems.

a. Closed-circuit systems

The closed-circuit indirect calorimetry requires the participant to be isolated from the external environment such that the participant's air intake is isolated from outside air. Essentially, this consists of a prefilled (100% oxygen) closed system called the spirometer through which the participant breathes using a specialized mouthpiece (Jeukendrup and Gleeson, 2010). With each breath, O_2 is consumed while CO_2 is produced and maintained in a filter in the spirometer. As a result, the gradual reduction of the gas volume inside the spirometer will be used as a measure for the rate of oxygen consumption (Valanou et al., 2006). This method is more suitable for measuring the resting energy expenditure (Abdelhamid, 1999; Valanou et al., 2006; Jeukendrup and Gleeson, 2010) and it is rarely used nowadays (Levine, 2005).

b. Confinement systems

Confinement systems, also known as respiratory chambers, are fully equipped rooms (e.g., a bed, chair, television, radio etc.) designed mainly for measurement of a complete energy balance which may last for several days (Jeukendrup and Gleeson, 2010). The chamber is sealed gas-tight with a known volume, where sufficient air continuously flows into the chamber to maintain the minimum amount of oxygen (Levine, 2005; Jeukendrup and Gleeson, 2010). Changes in O_2 and CO_2 concentrations inside the chamber over time are used to calculate the amount of oxygen consumed and carbon dioxide produced. This method produces measurements with errors of approximately 2% (Levine, 2005).

c. Total collection systems

A total collection system is one of the indirect calorimetry techniques, which uses either a portable flexible bag or a sealed rigid structure to collect participant's expired air for content analysis (Levine, 2005). One of the most widely used total collection systems, most notably used in small population studies is the Douglas bag technique, which is also considered a gold standard for open-circuit indirect calorimetry (Miller, 2005; Valanou et al., 2006). The Douglas bag technique consists of a plastic bag, a three-way valve, a nose clip and a mouthpiece. The participant breathes through the valve such that the exhaled air is exhaled into and collected in the plastic bag. The volume of the exhaled air as well as the concentrations of O_2 and CO_2 in the bag are used to determine the amount of oxygen consumption and thereby measures the energy expenditure (Valanou et al., 2006).

d. Open-circuit systems

In open-circuit spirometry, the system is not isolated from outside air such that the participant inhales ambient air with known concentrations (0.03% CO_2, 20.93% O_2 and 79.04% N_2) (Jeukendrup and Gleeson, 2010) and exhales into a separate outlet line (Dauncey and James, 1979; Miller, 2005). The difference in the O_2 and CO_2 contents between the inhaled and exhaled gases is used to determine the amount of oxygen consumed, which determines the energy expenditure. The open-circuit indirect calorimetry can take several forms from which ventilated open-circuit systems and expiratory collection systems are the most important ones (Simonson and DeFronzo, 1990; Abdelhamid, 1999; Ainslie et al., 2003; Levine, 2005; Johnston, 2006; McArdle et al., 2010).

Determining the energy expenditure using the ventilated open-circuit system involves four steps (Levine, 2005). The first step is to collect the exhaled air which varies depending on the experiment. The simplest way to collect the exhaled air is to use a mouthpiece, mask and transparent hood worn by the participant, and is therefore known as the ventilated hood system. However, the most complicated approach to collecting the exhaled air is to place the participant inside a chamber of known volume, this process is referred to as whole-body indirect calorimetry. The second step includes extracting the exhaled air from the hood collection device using a pump to record the flow rate. The third step is to mix the exhaled air using a fan. Finally, the concentrations of O_2 and CO_2 within the mixed expired air are analysed. The measured flow rate and percentages of O_2 and CO_2 in the mixed exhaled air are used to determine the VO_2 (Valanou et al., 2006). The estimation error involved in this technique ranges from 0.5% to 2% (Levine, 2005). Due to its high accuracy, the whole-body indirect calorimetry is considered a gold standard technique for measuring EE (Dauncey and James, 1979; Spurr et al., 1988; Ceesay et al., 1989; Westerterp et al., 1994; Bitar et al., 1996; Morio et al., 1997; Garet et al., 2005).

Expiratory collection systems include portable devices (spirometers) that are designed to measure oxygen consumption and carbon dioxide production in free-living individuals. These mainly consist of a mask and a one-way valve for the exhaled airflow. In general, portable spirometers (e.g., Cosmed K2, MedGem, Deltatrac, Metamax and Oxylog) have the ability to provide breath-by-breath inhaled/exhaled gas measurements during rest and different levels of activities (Miller, 2005; Valanou et al., 2006). The accuracy and reproducibility of the portable spirometers were tested in several studies. For instance, Wells and Fuller (1998) found that the Deltatrac system yielded a reproducibility error of less than 3% and 2% for measuring VO_2 and VCO_2, respectively (Johnston, 2006). The MedGem portable spirometer was tested against the Douglas bag technique but they showed no significant difference in measurements (Branson and Johannigman, 2004; Johnston, 2006). McLaughlin et al. (2001) showed that the Cosmed K4 portable system overestimated the VO_2 values measured by the Douglas bag technique during exercise. The computerized instrumentations are other forms of the expiratory collection systems and they are applicable in laboratory settings where the participant undergoes any type of activity. The monitoring of a participant's breathing and ventilation, as well as defining the contents of inhaled and exhaled air and the resulting VO_2 are determined using a computer system (Johnston, 2006).

2.2.1.3 Non-calorimetric methods

Non-calorimetric methods are used to estimate the energy expenditure from other related variables (Levine, 2005). One of the most accurate non-calorimetric methods is considered a standard reference which is known as the doubly labelled water method (Schulz et al., 1989; Livingstone et al., 1990; Van den Berg-Emons et al., 1996; Davidson et al., 1997; Morio et al., 1997; Garet et al., 2005). The doubly labelled water technique is based on the premise that the oxygen in exhaled CO_2 and in body water are in rapid isotopic equilibrium according to the following equation (Lifson et al., 1955; Levine, 2005; Johnston, 2006):

$$CO_2 + H_2O \leftrightarrow H_2CO_3 \qquad (2.1)$$

Accordingly, this method is based on monitoring a standardized amount of the two stable isotopes (^{2}H and ^{18}O) which are regularly mixed with the normal hydrogen and oxygen in the body water or $^{2}H_2{}^{18}O$ (Valanou et al., 2006). During energy expenditure, the body produces water and carbon dioxide. Consequently, the isotope ^{2}H is eliminated in the form of water (i.e., urine and sweat) at the same rate of water loss. Nevertheless, the isotope ^{18}O is eliminated in the form of both water (i.e., urine and sweat) and carbon dioxide at a faster washout rate. By analysing urine, it is possible to measure the differences in the washout rates of both isotopes and determine the CO_2 production from which EE can be calculated using established equations (Schoeller and Van Saten, 1982; Speakman, 1998; Miller, 2005; Valanou et al., 2006).

2.2.2 Estimation methods for assessing physiological demands

The existing literature on the subject has clearly demonstrated the difficulty in measuring the amount of oxygen consumed by individuals in actual work environments. This problem has been at the forefront of research since the early fifties, at which point Lehmann investigated the problem of evaluating oxygen consumption within particular work environments (Malchaire et al. 1984). He proposed tables to predict the oxygen consumption of an individual as well as the resulting amount of oxygen consumed by an individual while performing different types of activities (Lehmann, 1953). The energy expenditure of individuals was estimated either by breaking down the task into elementary movements and then using the table to sum up the energy cost of these elementary movements or, alternatively, by comparing the task to similar situations from the existing literature where average VO_2 values already exist (Malchaire et al. 1984). Although using the tables approach may indicate the most difficult work period, it can be misleading when estimating the average energy expenditure sustained over a longer period of time (Malchaire et al. 1984).

The use of HR measurements as a means to estimate metabolic rate was first studied by Benedict in 1907 (Spurr et al. 1988). The possibility of estimating energy expenditure from HR was later investigated by many authors (Bradfield, 1971; Bradfield et al., 1971; Payne et al., 1971). Cross-validation studies, however, have demonstrated poor estimation accuracy attributable to the lack of devices to accurately measure HR over short intervals (Spurr et al. 1988; Ceesay et al., 1989). The advancements in the technology and development of computers and HR recording device technologies have allowed accurate estimation of HR over short intervals (e.g., minute-by-minute). Studies have demonstrated the importance of the relationship between energy expenditure and heart rate for a wide variety of activities (Rodahl et al., 1974; Evans et al., 1983; Gordon et al., 1983; Astrand and Rodahl, 1986; Schulz et al. 1989). And, in addition to the well-established VO_2-HR relationship, especially at moderate to high intensity (Freedson and Miller, 2000), HR is considered the least invasive and most economically viable and easily measurable physiological variable related to oxygen consumption (Valanou et al., 2006; Firstbeat Technologies Ltd., 2007). With the advancement of technology, HR recording intervals can be significantly small (e.g., second-by-second) enough to allow for an accurate estimation of VO_2. In addition, the storage capacity of HR monitors can last up to four days and thus provide information about the duration, frequency and intensity of work as well as calculate total energy expenditure (Valanou et al., 2006). Therefore, nowadays, the relationships between different types of heart rate variables and the corresponding oxygen consumption variables are used to estimate oxygen consumption.

2.2.2.1 Using individual calibration

Different types of VO_2-HR relationships (calibration curves) have been proposed, such as: linear (Schulz et al. 1989; Bouchard and Trudeau, 2008), exponential (Li et al. 1993; Bitar et al. 1996; Garet et al. 2005), logarithmic (Schulz et al. 1989), 2nd order polynomial (Schulz et al. 1989; Bitar et al. 1996; Davidson et al. 1997), 3rd order polynomial (Bitar et al. 1996; Garet et al. 2005), and finally the Flex-HR method (Spurr et al. 1988; Ceesay et al. 1989; Schulz et al. 1989; Livingstone et al. 1990; Van den Berg-Emons et al. 1995, 1996; Fogelholm et al. 1998). The Flex-HR method is considered the most commonly employed method used to estimate VO_2 from HR recordings (Garet et al. 2005). This method assumes a linear relationship between HR and VO_2 above a transition point (Flex point) and a more variable relationship below this point (Garet et al. 2005; Valanou et al., 2006). Therefore, to estimate VO_2 and/or EE from HR, the linear regression equation is used above the Flex point, and the average of a series of VO_2 values obtained during rest is used below it (Valanou et al., 2006). The Flex point is empirically defined as the average of the lowest HR value during exercise and the highest HR value during rest (Garet et al. 2005; Valanou et al., 2006). The difficulty with this method is in determining the Flex point accurately so that the relationship between HR and VO_2 during different work intensities is obtained accurately.

One of the first attempts to investigate this problem was a study conducted by (Spurr et al. 1988) to evaluate the total daily energy expenditure and energy spent in any given activity using minute-by-minute HR recording. The study involved individual calibration of 22 participants, where the VO_2-HR relationships were established for each individual using the Flex-HR method. During the calibration process, various Flex points were applied in the calculation of VO_2, which includes: 1) the average of the highest HR at rest and the lowest HR during exercise on the bicycle ergometer, while HR at rest was determined as the mean of several resting values during lying, sitting on a chair, standing, and sitting on the bicycle ergometer; 2) the value obtained by looking at the plotted values of VO_2 with HR; 3) a series of values obtained from (the average of the highest HR at rest and the lowest HR during exercise) +5, +10, +15, and +20 beats/min. The different individual calibration curves (associated with different Flex points) were tested and compared with the referenced method initially used to determine VO_2 and EE, better known as the whole-body indirect calorimeter. Results showed that setting the Flex point as (the average of the highest HR at rest and the lowest HR during exercise) +10 yields the highest correlation coefficient (r) and a lowest standard error for the estimate (SEE). The authors concluded that using the Flex-HR method to estimate EE provides a close estimate of actual EE even in small groups and reveals information on the patterns of daily activity that are not afforded by other methods.

A modified Flex-HR method for estimating VO_2 and total EE was proposed by (Ceesay et al. 1989). Minute-by-minute HR recording was used to establish (20 participants) individual VO_2-HR relationships (individual calibration) in order to estimate VO_2 and total EE. Individual calibration curves were established under more rigorous conditions by imposing a variety of different exercise types (Cessay et al. 1989). In addition, the Flex point was defined as the mean of the highest HR during the standing measurements and the lowest HR during stepping measurements. For low levels of activity, the mean VO_2 was measured while the participant was lying down, sitting and standing at rest to estimate sedentary EE. However, for higher activity levels, individual calibration curves were used to estimate individual activity EE. The authors concluded that the Flex-HR method provides satisfactory predictive power and low cost for VO_2 and EE estimation which make it suitable for many field applications.

A study conducted by Schulz et al. (1989) estimated EE from HR recording. In order to estimate the daily EE, the relationship between HR and VO_2 was established for each individual using four different types of calibration curves: 1) first order regression of VO_2 on HR for each participant, 2) second order regression of VO_2 on HR for each participant, 3) two linear regression lines for VO_2 on HR (one for the data obtained during light activities and rest and the second for the data determined during exercise). This method could be considered a modification of the Flex-HR method, 4) first order regression of log (VO_2) on HR for each participant. The authors concluded that using the first order regression of log (VO_2) on HR for individual calibration produces more accurate results than the other three calibration curves.

In 2008, Bouchard and Trudeau investigated the estimation of EE in working environments using two different methods: accelerometry and HR-based method. The latter is based on an individual calibration process in which a regression equation was established for each worker from the VO_2-HR data measured in the laboratory before a regular work shift. Although the two methods are considered practical and easy to use in the field, individual results usually differed from each other, especially when the mean job intensity (% of HR over resting HR) was not within 16% and 23% higher than resting HR (Bouchard and Trudeau, 2008). This study had several limitations: it included small number of individuals which might limit the potential for the generalization of results, it only included a single shift work, and the fact that results were not compared to a reference method (Bouchard and Trudeau, 2008).

2.2.2.2 Using general models

Although all the HR-based methods discussed above have been widely accepted to energy expenditure estimation, they have always been restricted to small sample size studies. The reason for this is the fact that these HR-based methods require individual calibration which is costly, time consuming and requires sophisticated equipment. The individual calibration process to determine the VO_2-HR relationship takes at least 45 minutes for each individual (Rennie et al. 2001). Therefore, HR-based methods that require individual calibration are not suitable for studies estimating energy expenditure in work environments with large populations.

Several attempts have been made to estimate energy expenditure using group calibration methods (Li et al., 1993; Luke et al., 1997; Rutgers et al., 1997; Rennie et al., 2001; Keytel et al., 2005). Li et al. (1993) have developed a prediction equation using heart rate/energy expenditure calibration based on data collected from 40 female workers. In addition to the general prediction equation, the individual calibration process was performed to analyze the variation of EE-HR relationship between and within participants. Li and colleagues found poor levels of agreement between the EE values estimated by the group calibration method and those estimated by the individual calibration method, which might be due to the small sample size incorporated in the modeling. They concluded that in order to estimate an individual’s energy expenditure based on HR monitoring, one should use the individual calibration process. Moreover, to estimate an individual’s EE in different situations and separate instances, the individual calibration process would benefit from being repeated for each instance.

In 1997, Luke and colleagues developed a single prediction equation based on a group of 10 participants to estimate VO_2 above the resting heart rate by simultaneously monitoring HR and motion. They concluded that incorporating the motion data to estimate VO_2 was beneficial only during lower heart rates. Moreover, their model was based on a laboratory study and not on easily measured variables. Rutgers et al. (1997) derived a calibration curve that describes the EE-HR relationship based on a group of 13 elderly women. Results showed that the EE estimation using the group calibration curve was not significantly correlated with EE estimation using the individual calibration curves or the activity questionnaire method. Therefore, Rutgers and colleagues concluded that the use of a group calibration equation was an inaccurate means to estimate energy expenditure. Hiilloskorpi et al. (1999) developed a general HR-based prediction equation to estimate energy expenditure during physical activity. Forty-two women and forty-five men were considered for the development of the general equation. The effect of other factors (i.e., age, weight, gender and mode of exercise) on the energy expenditure during activity was investigated. Results indicated the significant impact of gender and weight on the EE-HR relationship and therefore it was recommended to incorporate these two factors in addition to HR for EE estimation (Hiilloskorpi et al., 1999). In 2001, Rennie and colleagues developed a prediction equation for estimating energy expenditure from heart rate measurements based on 789 individuals. Similarly, age, weight and gender, when considered in addition to resting heart rate, had a significant impact on the relationship between heart rate and energy expenditure. Unlike previous studies, Rennie et al.'s model was validated on an independent sample of 97 individuals and was reasonably accurate. However, this model was restricted to 40-70 year age range. In a more recent study, Keytel et al. (2005) used mixed-model analyses to derive two linear equations to estimate energy expenditure from HR without individual calibration. A measure of physical fitness was considered in one of the developed models. Results identified gender, heart rate, weight, age as factors that best predict the relationship between heart rate and energy expenditure. Results also showed that including individuals' fitness level in the prediction model increased the correlation between the measured EE and the estimated EE from 0.857 to 0.913. In general, most of the previous modeling efforts were based on linear prediction models using regression and mixed-model analyses which, although easy and simple to apply, have several limitations such as the requirement of large sample size and the inability of capturing nonlinearity, uncertainty and true relationship between physiological variables in the human physiological system (Shimizu and Jindo, 1995; Park and Han, 2004).

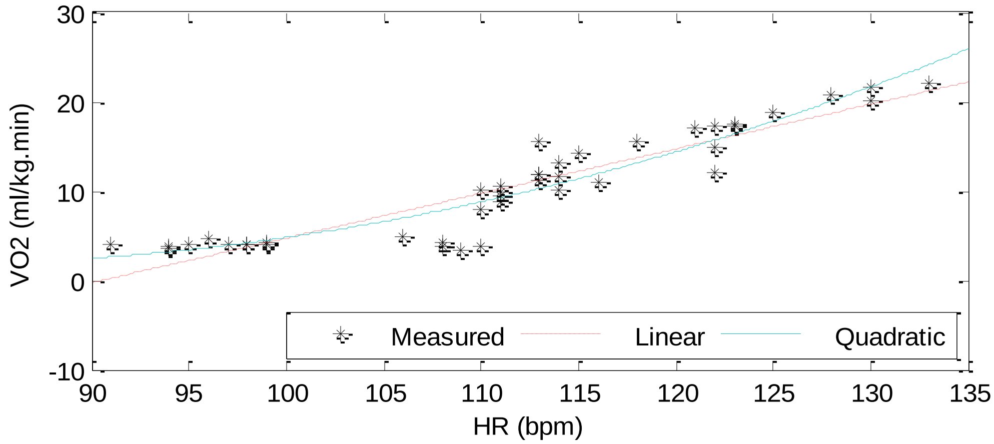

Figure 2-2: Relationship between HR and VO_2

2.3 Evaluating physiological demands of physical activities

Nowadays, evaluating the physiological demands of work is typically achieved by describing the work qualitatively based on its intensity (i.e., work classification). There are two main methods for classifying work rate: using absolute and relative values.

2.3.1 Using absolute values

The first method is based on energy expenditure that is measured indirectly by measuring oxygen consumption. Christensen (1964) and Astrand and Rodahl (1986) proposed limits and norms of oxygen consumption to classify work rate (Table 2.1). Additionally, the American Industrial Hygiene Association (AIHA, 1971) proposed norms of minute energy expenditure to assess workload and classify work rate (Table 2.1). Other studies have proposed norms of energy expenditure based on 8 hours workday such as Hettinger (1970) and AIHA (1971). In the second method, work rate is classified based on variables that have a linear relationship with energy expenditure, such as HR (Table 2.1) (Grandjean, 1980). HR provides an easy and practical means for workload evaluation since it can be measured easily (Grandjean, 1980). Many researchers, however, have argued that the use of absolute workload maybe a vague guideline for work design since it ignores the inter-individual variability in terms of the physical capacity of each individual. Therefore, other researchers have suggested taking the relative workload of a task into consideration instead. This can be achieved by expressing an individual's oxygen consumption while working as a percentage of his/her maximum oxygen consumption (VO_{2max}). This ratio is called the relative oxygen consumption (%VO_{2max}). VO_{2max}, also known as aerobic capacity, is the highest level of oxygen consumed by individuals during dynamic work activities with large muscle groups. Studies have shown that VO_{2max} is dependent on individual factors (e.g., sex, age, body dimension, and inheritance), environmental factors (e.g., intensity, duration, and technique of exercise), and adaption through training (Abdelhamid, 1999). VO_{2max} is considered as one of the best indicators of an individual's aerobic and physical fitness (Astrand and Rodahl, 1986; Jackson et al., 1990; McArdle et al., 2010).

2.3.2 Using relative values

The relative oxygen consumption provides an accurate means for workload evaluation and therefore is considered as the gold standard for classifying work rate (U.S. Department of Health and Human Services, 1996; Haskell and Pollock, 1996; Pollock et al., 1998) (Table 2.1). In addition to work rate classification, different norms (in terms of %VO_{2max}) for a typical 8-hour workday are reported in the existing literature. Astrand and Rodahl (1986) recommended that an individual cannot tax more than 30-40% of VO_{2max} during 8 hr workday without feeling physical fatigue. They also proposed a value of 50% of VO_{2max} as the upper limit of endurance tolerance. Bonjer (1971) proposed a limit of 30% of VO_{2max} as the acceptable limit of dynamic muscular work. Several researchers (e.g., Michael et al., 1961; Bink 1962; Lehmann, 1953) suggested that 33% of VO_{2max} as the acceptable workload for a general physical 8 hr workday (Wu and Wang, 2002). Although the classification method based on %VO_{2max} is accurate, it requires measurements of VO_2 values during work as well as each individual VO_{2max}, and is therefore considered costly, time consuming and potentially hazardous for unfit individuals.

Several studies have explored the use of relative heart rate variables to estimate relative oxygen consumption and/or relative energy expenditure (Panton et al., 1996; Swain and Leutholtz, 1997; Swain et al., 1998; Rotstein and Meckel, 2000; Wu and Wang, 2002; Garet et al., 2005; Pettitt et al., 2008). The relationships between percentage of maximal heart rate (%HR_{max}), percentage of heart rate reserve (%HRR) and %VO_{2max} during submaximal treadmill exercise were examined (Panton et al., 1996). The percentage of heart rate reserve is defined as:

$$(HR_{work} - HR_{rest})/(HR_{max} - HR_{rest}) \times 100\% \qquad (2.2)$$

where HR_{max} is the maximum heart rate, HR_{rest} is the resting heart rate, and HR_{work} is the average heart rate during work. Regression analysis was implemented to establish the relationship between $\%HR_{max}$ and $\%VO_{2max}$ as well as %HRR and $\%VO_{2max}$. Results indicated that there is considerable variability among these different measures of exercise intensity and that $\%HR_{max}$ more closely represents $\%VO_{2max}$ than %HRR in elderly (Panton et al., 1996).

The concept of % HRR was first introduced as a method of exercise prescription in 1957 (Karvonen et al., 1957). This study examined the heart rate responses to exercise training by six male adults. The recorded heart rates were expressed as a percentage of the difference between HR_{max} and HR_{rest}, which is called Karvonen heart rate. Although no conclusions regarding the relationship between %HRR and $\%VO_{2max}$ in this study were possible, traditionally, it is accepted that %HRR was equivalent to $\%VO_{2max}$. For this reason, many researchers have examined the validity of this relationship. Two studies (Belman and Gaesser, 1991; Panton et al., 1996) supported the lack of equivalency between %HRR and $\%VO_{2max}$. Another study conducted by (Davis and Convertino, 1975) supported the equivalency between %HRR and the percentage of oxygen consumption reserve ($\%VO_{2R}$). The percentage of oxygen consumption reserve is defined as:

$$(VO_{2work} - VO_{2rest})/(VO_{2max} - VO_{2rest}) \times 100\% \qquad (2.3)$$

where VO_{2max} is the maximum oxygen consumption, VO_{2rest} is the resting oxygen consumption, and VO_{2work} is the average oxygen consumption during work. Swain and Leutholtz (1997) first reported that %HRR is equivalent to $\%VO_{2R}$, and not $\%VO_{2max}$ during cycling exercise in healthy, young males and females (Dalleck and Kravitz, 2006). This study points to a comparison between the range of HR from rest to the maximum with a range of VO_2 from zero to the maximum to introduce an error in the estimation of $\%VO_{2max}$ from %HRR (Rotstein and Meckel, 2000). However, in accounting for the fact that VO_2 at rest is not zero, it was demonstrated that %HRR is closer to $\%VO_{2R}$ than $\%VO_{2max}$. These findings were confirmed during treadmill exercises in healthy participants (Swain et al., 1998) and in cardiac patients (Brawner et al., 2002) as well as during elliptical crosstrainer exercises (Dalleck and Kravitz, 2006).

It bears mentioning that Swain et al. (1998) and Brawner et al. (2002) demonstrated that the relationship between %HRR and $\%VO_{2R}$, though statistically different, is closer to the line of identity than %HRR and $\%VO_{2max}$. They suggested that there may be a mode effect (cycle vs.

Treadmill), which would explain the line of identity differences between studies. However, several studies, such as Davis and Convertino (1975) and Dalleck and Kravitz (2006), have argued against this assumption. In general, these studies (Swain and Leutholtz, 1997; Swain et al., 1998; Brawner et al., 2002; Dalleck and Kravitz, 2006) recommended the use of %HRR to estimate relative oxygen consumption reserve for exercise prescription and to determine work rate.

Rotstein and Meckel (2000) examined the relationship between %HRR and the corresponding $\%VO_{2R}$ in arm exercise and compared this relationship to that associated with running. Results indicated that the prediction accuracy of $\%VO_{2R}$ from %HRR is lower in arm exercise than it is during running. Therefore, it was demonstrated that when a low muscle mass is employed, there is a decrease in the accuracy of the prediction of $\%VO_{2R}$ from %HRR (Rotstein and Meckel, 2000).

Garet et al. (2005) investigated the validity of the cardiac cost method for total and relative EE estimation (Chamoux et al., 1985; Kamal et al., 1991). Linear regression analysis was used to establish individual relationships between cardiac reserve (%HRR) and energetic reserve ($\%VO_{2R}$) and between corrected cardiac reserve (%CHRR) and $\%VO_{2R}$. The %CHRR was calculated as: $[(HR\text{-}HR_{rest}+15)/(HR_{max}\text{-}HR_{rest}+15)]100$. The other types of relationships considered were 3^{rd} order polynomial and Flex-HR method. This study demonstrated that relative physical workload can be accurately estimated from HR recordings when expressed in %CHRR between 15% and 65% and EE can be accurately estimated using the %CHRR method (Garet et al., 2005).

In light of the previous discussion, for practical applications, several studies recommended the use of %HRR to estimate $\%VO_{2max}$ for work evaluation and classification (Haskell and Pollock, 1996; Pollock et al., 1998; American College of Sports Medicine (ACSM), 2006). The estimation of HR_{max} has been broadly accepted as a computation of: 220-age (Fox et al., 1971; Londeree and Moeschberger, 1982; Tanaka et al., 2001; Robergs and Landwehr, 2002; McArdle et al., 2010).

Table 2.1: Norms for work rate classification

Assessment of work load	VO_2 (L/min)		EE (kcal/min)	EE (kcal/8hr)		HR (bpm)			$\%VO_{2max}$ or %HRR (%)
	Christensen (1964)	Astrand and Rodahl (1986)	AIHA (1971)	AIHA (1971)	Hettinger (1970)	Christensen (1964)	AIHA (1971)	Astrand and Rodahl (1986)	U.S. Department of Health and Human Services, (1996) and ACSM (2006)
Sitting	___	___	1.5	< 720	___	___	60 – 70	___	___
Very low (Very light)	0.25 – 0.3	___	1.6 – 2.5	768 – 1200	___	60 – 70	65 – 75	___	0 - 24
Low (Light)	0.5 – 1.0	< 0.5	2.5 – 5.0	1200 – 2400	< 1000	75 – 100	75 – 100	< 90	25 - 44
Moderate	1.0 – 1.5	0.5 – 1.0	5.0 – 7.5	2400 – 3600	1000 - 1600	100 – 125	100 – 125	90 – 110	45 - 59
High (Heavy)	1.5 – 2.0	1.0 – 1.5	7.5 – 10.0	3600 – 4800	1600 - 2000	125 – 150	125 – 150	110 – 130	60 - 85
Very high (Very heavy)	2.0 – 2.5	1.5 – 2.0	10.0 – 12.5	4800 – 6000	> 2000	150 – 175	150 – 180	130 – 150	> 85
Extremely high (Unduly heavy)	2.5 – 4.0	> 2.0	> 12.5	> 6000	___	> 175	> 180	150 - 170	___

Note. VO_2 (L/min) = Oxygen consumption in litre per minute; EE (kcal/min) = Energy expenditure in kilocalorie per minute; EE (kcal/8hr) = Energy expenditure in kilocalorie per 8 hours; HR (bpm) = Heart rate in beat per minute; $\%VO_{2max}$= Percentage of maximal oxygen consumption; %HRR= Percentage of heart rate reserve.

2.4 Other non physical exercise related factors affecting heart rate

Many researchers have investigated the factors that may affect the relationship between heart rate and oxygen consumption and may affect the VO_2 estimation, as a result. Studies have shown that several factors affect the heart rate without necessarily affecting oxygen consumption. These factors include age, body size (Karpovich and Sinning, 1971; Li et al., 1993; Garet et al., 2005), body position (Karpovich and Sinning, 1971; Ceesay et al., 1989; Rayson et al., 1995; Garet et al., 2005; Valanou et al., 2006), food intake (Karpovich and Sinning, 1971; Wu and Wang, 2002), time of day (Karpovich and Sinning, 1971), emotions (Moss and Wynar, 1970; Karpovich and Sinning, 1971; Gaudemaris et al., 1998; Wu and Wang, 2002; Garet et al., 2005; Valanou et al., 2006), ambient temperature (Moss and Wynar, 1970; Gaudemaris et al., 1998; Smolander and Louhevaara, 1998; Wu and Wang, 2002; Garet et al., 2005; Valanou et al., 2006; Smolander et al., 2008), size of active muscle mass (Smolander and Louhevaara, 1998; Valanou et al., 2006; Smolander et al., 2008), static work, dynamically changing work rate, psychological factors (Smolander and Louhevaara, 1998; Smolander et al., 2008), high humidity, dehydration, type of the muscle group, type of muscle contraction, fatigue, physical fitness (Wu and Wang, 2002; Valanou et al., 2006), caffeine (Li et al., 1993; Garet et al., 2005; Valanou et al., 2006), training level, alcohol and cigarette consumption (Li et al., 1993; Garet et al., 2005). As a result, these factors may lead to an overestimation of oxygen consumption. It is advisable to be cautious and either control or take these factors into consideration when using heart rate measurements for energy expenditure estimations.

The majority of these factors, such as psychological factors, emotional stress, size of active muscle mass, type of muscle group, type of muscle contraction, static work, dynamically changing work intensities, illness, humidity, and body posture, influence HR at low activity levels (Melanson and Freedson, 1996; Montoye et al., 1996; Smolander and Louhevaara, 1998; Keim et al., 2004; Smolander et al., 2008). However, it should be noted that the effect of these variables on HR becomes negligible at moderate to high activity levels (Freedson and Miller, 2000; Valanou et al., 2006). Practically, it is not possible to consider all factors that influence the relationship between HR and VO_2. For these reasons, we focused on important factors that are directly related to increased work demands and are commonly encountered in work environments as the nucleus of our research. Factors such as gender, age, weight, fitness level were taken into account during the modeling process (as such, these were incorporated into models as input variables). The thermal stress was handled by refining HR measurements from the thermal pulse using the method proposed by Vogt et al. (1970, 1973). In addition, participants were required to follow a strict set of instructions during the research period to control factors such as fatigue, food intake, hydration, caffeine, alcohol, tobacco, and medication. For example, participants were asked to refrain from strenuous exercise and alcohol consumption 12 hours before any given experiment session. Also, participants were asked to limit the consumption of caffeine and to drink additional quantities of water the evening before and the day of the experiment session. During morning sessions, participants were required to perform the tests before breakfast. For afternoon sessions, participants performed the tests prior to lunch time and at least 3.5 hours after lunch. Most importantly, participants were instructed to eliminate tobacco use and limit medication the day of the experiment session.

CHAPTER 3: ARTIFICIAL INTILLEGENCE AND SOFT COMPUTING

3.1 Introduction

Recently, a new challenge has arisen, one posed by the beginning of a new era of information technology concerned with the rapid processing of statistical and cognitive information (originating from the human cognitive faculty) (Sinha and Gupta, 2000). As a result, current research focus is shifting towards a broad area of research within the artificial intelligence (AI) discipline called soft computing (SC) (Cordon et al., 2011). One of the key figures in the SC field is Lotfi Zadeh who defined SC as "*an emerging approach to computing which parallels the remarkable ability of the human mind to reason and learn in an environment of uncertainty and imprecision*" (Zadeh, 1992; Jang et al., 1997). SC is mainly concerned with designing hybrid intelligence systems that have the ability to handle imprecision, uncertainty, partial truth and approximation with an ultimate objective of achieving tractability, robustness, and completeness at a low solution cost and a better bond with reality (George and Cardullo, 1999; Eberhart and Shi, 2007; Cordon et al., 2011). The main intelligent systems that constitute the SC are: fuzzy logic (FL) or fuzzy systems, artificial neural networks (ANN), evolutionary computing, machine learning and probabilistic reasoning (i.e., genetic algorithm, chaos theory, belief nets and learning theory). It is important to note that no matter in which combination intelligent systems interact; they complement rather than compete with each other. This indicates that each intelligent system contributes, at different organizational levels, with its own specific strengths, to a hybrid intelligent system with diversified ability. Therefore, SC is considered an emerging mathematical approach with stronger capabilities to deal with the inherent complexity of modeling human related systems (i.e., physiological system) (George and Cardullo, 1999). The following subsections summarise the main components of the SC intelligent systems that are used in this dissertation, namely fuzzy systems, artificial neural networks and neuro-fuzzy systems.

3.2 Fuzzy systems

The problem of estimating the energy expenditure or oxygen consumption using heart rate measurements is often accompanied by some degree of uncertainty, inaccuracy and nonlinearity.

This due to many external sources that affect the VO_2-HR relationship in the human physiological system, such as: fatigue, stress, heat and fitness level. Fuzzy systems have proven their efficiency in confronting real-life problems involving uncertainty, vagueness and nonlinearity. For this reason, their use and value in many fields is increasing, and they are especially common in medical and biomedical applications (Yildiz et al., 2009). However, their use in the human work physiology field is very limited.

The following subsections describe the concept of fuzzy systems and their mechanism in representing, manipulating and drawing inferences from ambiguous information in order to make a decision or take an action. First I present a brief summary of the fuzzy set theory and the concept of fuzzy logic, followed by a description of the fuzzy inference system and its main components.

3.2.1 Fuzzy set theory

The first attempt to tackle problems associated with classical two-valued logic (0 and 1) was by Lotfi Zadeh in his 1965 introduction to fuzzy set theory (Zadeh, 1965). Fuzzy sets are considered to be an extension of crisp sets because they provide a natural framework for representing the imprecision and ambiguities associated with real-world applications. Fuzzy sets, unlike crisp sets, can be described as sets without sharp and precisely defined boundaries. The degree of belonging, also called degree of membership, of an element to a fuzzy set ranges from 0 to 1, indicating that an element can belong to more than one fuzzy set at the same time with different degrees of belonging. However, in a crisp set, an element either “belongs to” or “does not belong to” the set with a degree of membership that is either 1 or 0 respectively. The degree of membership is assigned to each point in the input space (universe of discourse) using a membership function (MF). Thus, a membership function can be described as a function that is used to represent any crisp input with a value that ranges from 0 to 1. Although there are different membership functions, the following are the most commonly used membership functions:

- Triangular membership functions

This membership function is considered the simplest since its design requires the least number of straight lines based on three points (one centre point and two points on either side). For any variable δ, the triangular membership function depends on three parameters: α, β and γ such that,

$$f(\delta;\ \alpha,\beta,\gamma) = \begin{cases} 0 & \delta \le \alpha \\ \frac{\delta-\alpha}{\beta-\alpha} & \alpha \le \delta \le \beta \\ \frac{\gamma-\delta}{\gamma-\beta} & \beta \le \delta \le \gamma \\ 0 & \gamma \le \delta \end{cases} \qquad (3.1)$$

Figure 3-1 shows a triangular membership function representing the variable age in fuzzy form.

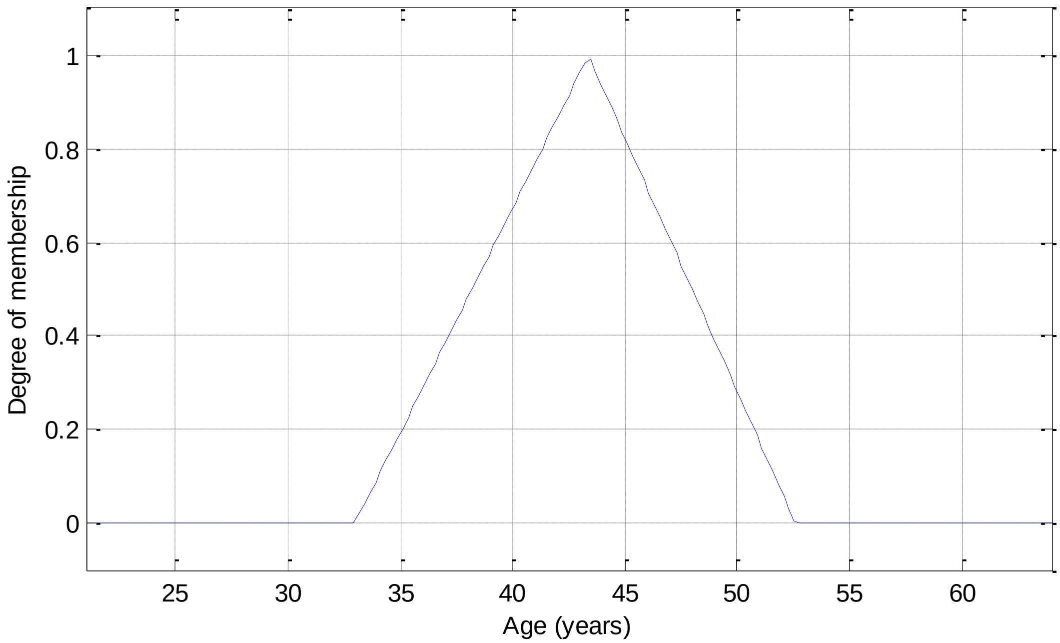

Figure 3-1: Triangular membership function

- Trapezoidal membership functions

The trapezoidal membership function is considered as a truncation of the triangular membership function. It depends on four parameters: α, β, γ and σ such that,

$$f(\delta;\ \alpha,\beta,\gamma,\sigma) = \begin{cases} 0 & \delta \le \alpha \\ \frac{\delta-\alpha}{\beta-\alpha} & \alpha \le \delta \le \beta \\ 1 & \beta \le \delta \le \gamma \\ \frac{\sigma-\delta}{\sigma-\beta} & \gamma \le \delta \le \sigma \\ 0 & \sigma \le \delta \end{cases} \qquad (3.2)$$

Figure 3-2 shows a trapezoidal membership function representing the variable age in fuzzy form.

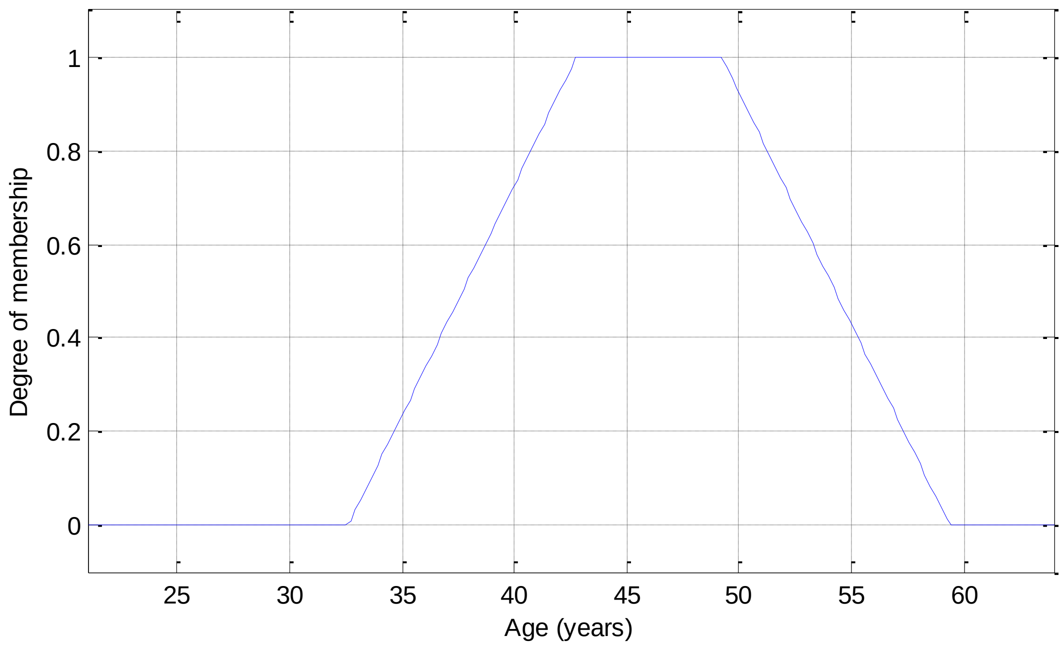

Figure 3-2: Trapezoidal membership function

- Gaussian membership functions

Gaussian membership functions are characterized as smooth and they have a nonzero value at all points. These functions depend on two parameters: σ and γ such that,

$$f(\delta;\ \sigma, \gamma) = e^{\frac{-(\delta-\gamma)^2}{2\sigma^2}} \qquad (3.3)$$

Figure 3-3 shows a Gaussian membership function representing a variable for age in fuzzy form.

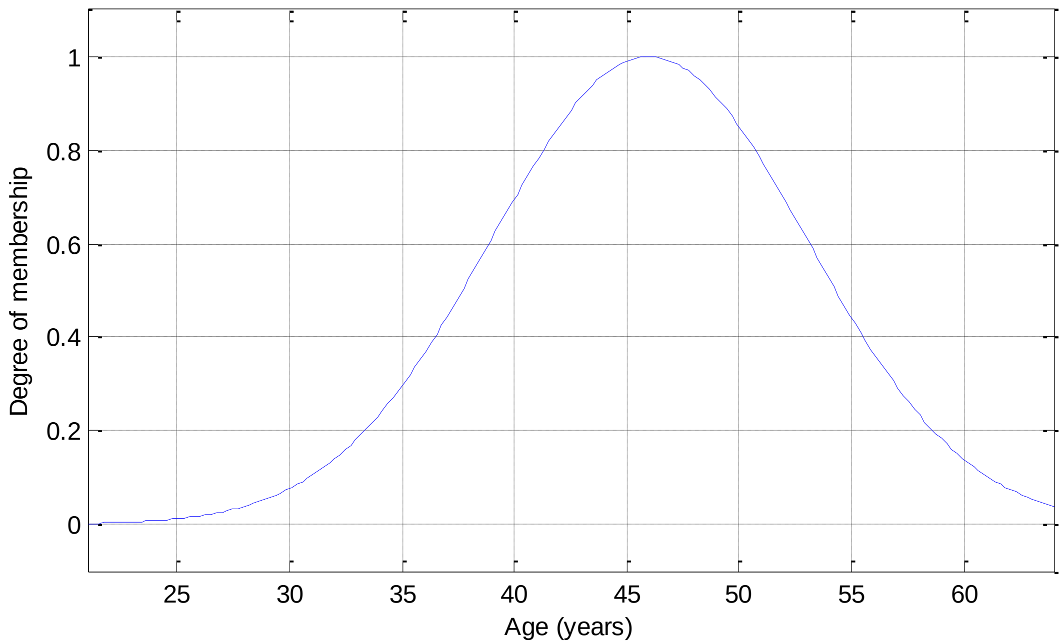

Figure 3-3: Gaussian membership function

It is worth mentioning that the development of the fuzzy set theory, according to Zimmermann (2001), progressed in two directions. The first direction was a theory-oriented direction where various original ideas and concepts contributed to the development of fuzzy set theory. In addition, extending fuzzy set theory as it applies to classical mathematical areas (e.g., algebra, graph theory and topology) helped enrich the field. The second direction was an application-oriented direction, known as fuzzy technology, where the fuzzy set theory constituted the base of many modeling, problem solving and data mining tools. Since this dissertation is concerned with the application side of the fuzzy set theory, it is useful to consider the following main goals of fuzzy technology according to Zimmermann (2001).

- Modeling of incompleteness of data and knowledge

This goal is considered one of the most important goals for using the fuzzy technology in solving real-world problems where the incompleteness of data and knowledge bases is often inherent to the nature of the problem. Mainly, two forms of incompleteness characterise real-world problems: incompleteness of data, called “imprecision” and incompleteness of knowledge, which is referred to as “uncertainty”. The former is caused either by a lack of appropriate data or the poor authenticity level of the sources, while the latter is caused by a lack of certainty relating to different pieces of knowledge (Konar, 2000). Besides fuzzy technology, there are claims that other methods are suited to modeling imprecision and uncertainty (e.g., probabilistic reasoning and certainty factor-based reasoning). Konar (2000) and Zimmermann (2001) suggested that uncertainty and imprecision can be modeled by different methods depending on several factors, such as the causes of incompleteness of data and knowledge, available information, as well as the requirements of the observer. According to them, fuzzy set theory is also one of the methods that can be used to model specific types of uncertainty and imprecision under specific conditions. More details can be found in (Zimmermann, 1997).

- Relaxation

Whereas conventional methods of modeling do not represent reality properly since they are based on dual logic (e.g., a data point either belongs or does not belong to a cluster), fuzzy set theory has been invoked to relax or generalize conventional methods (e.g., a data point can belong to more than one cluster with different degree of belongings). Examples include: relaxing mathematical programming to fuzzy mathematical programming (Zimmermann, 2001) and hard clustering to fuzzy clustering (Bezdek and Pal, 1992).

- Compactification

At present, many applications involve storing, recalling, presenting and processing vast amounts of data. This is often difficult especially with the limitation of current technology or human short-term memory. Fuzzy technology offers a solution to such limitations by reducing the complexity of the data such that it can easily be stored, processed and presented to an observer. This is achieved either by using linguistic variables or by fuzzy data analysis (e.g., fuzzy clustering) (Zimmermann, 2001).

- Meaning preserving reasoning

One of the main limitations of classical expert systems was their inability to process the meaningful linguistic expressions that are inherent to many real-world problems. This is mainly due to the inference engine which can only perform symbolic processing rather than knowledge processing (Zimmermann, 2001). With fuzzy set theory, inference engines are able to perform approximate reasoning where linguistic variables are used to describe words and sentences. This allows the inference engines to process meaningful linguistic expressions.

- Efficient determination of approximate solutions

Another main objective of fuzzy set theory is to provide efficient and affordable approximated solutions for real-world problems (Zimmermann, 2001). In the recent past, many studies have shown the validity of this proposition especially when considering the imprecision and uncertainty inherent to the problem. For instance, in the context of water flow modeling, Bardossy (1996) showed how the problem could be solved more efficiently using fuzzy rule based systems rather than differential equations.

3.2.2 Fuzzy logic

The general concept of fuzzy logic refers to the use of fuzzy systems to represent, manipulate, and draw inferences from imprecise and vague information in order to make decisions or take actions. In the narrower sense, fuzzy logic is described as the logic that uses soft linguistic systems variables (e.g., fast, high, hot etc.) and a continuous range of truth values between 0 and 1, instead of the conventional Boolean logic with two-valued sets (Ivancevic and Ivancevic, 2007). In 1973, Lotfi Zadeh introduced the concept of fuzzy logic, which originated from fuzzy set theory (Zadeh, 1973). Currently, fuzzy logic is considered one of the most efficient approaches for describing the behaviour of complex real-life systems that cannot be described mathematically or that are too difficult to be solved when represented mathematically. Therefore, fuzzy logic has attracted considerable attention in different fields and applications, such as modern information technology, production technique, decision making, pattern recognition, nonlinear approximation, diagnostic and data analysis, (Dubois and Prade, 1998; Kuncheva and Steimann, 1999; Yildiz et al., 2009).

The first step in developing fuzzy logic is to divide the input and the output domains into separate regions by using the membership functions. The various combinations of these membership functions in the input are then used to develop the logic. In opposition to Boolean logic, fuzzy logic is based on simple logical statements that are developed by combining input membership functions using simple logical operators, such as: AND (the binary equivalent of the minimum of two numbers) with OR (the equivalent of the maximum of two numbers) such that each logical statement is associated with a specific region within the divided output. These logical statements are expressed in the form of IF-THEN rules, which consist of two parts, the condition part (IF-Part) that makes up the premise or the antecedent, and the action part (THEN-Part) called the consequent. For instance, consider the following fuzzy IF-THEN rule:

$$IF\ X\ is\ A\ THEN\ Y\ is\ C$$

where A and C are linguistic values defined by the fuzzy sets associated with X (input) and Y (output) spaces respectively. Here, the clause (X *is* A) is called the antecedent clause where the fuzzy set A defines the fuzzy region covered by the rule. On the other hand, the clause (Y *is* C) is called the consequent clause where the fuzzy set C explains the fuzziness or vagueness of the rule output (Deng, 2002).

The concept of fuzzy logic can be easily applied based on fuzzy operators. Mainly, there are three types of fuzzy operations:

- Fuzzy complements:

This operation can be described as follows, let A be a set on X and $\mu(x)$ represents the degree the x belongs to A, then the fuzzy complement $\bar{\mu}(x)$ can be defined as the degree to which x does not belong to A.

- Fuzzy intersection or (t-norms)

The intersection of two fuzzy sets A and B can be defined as follows:

$$C = A \cap B$$

The fuzzy operators the can be used to represent the intersection operation are called triangular norms (t-norms).

$$\mu_{A\cap B}(x) = t[\mu_A(x), \mu_B(x)]$$

T-norms are two-valued functions from [0, 1] × [0, 1] that satisfy the following conditions:

a) Boundary conditions

$$t(0,0) = 0; t(\mu_A(x), 1) = t\big(1, \mu_A(x)\big) = \mu_A(x), x \in X$$

b) Monotonicity

$$t\big(\mu_A(x),\ \mu_B(x)\big)\ \le\ t\big(\mu_C(x),\ \mu_D(x)\big)$$

$$\text{if}\quad \mu_A(x) \le\ \mu_C(x)\ and\ \ \mu_B(x) \le\ \mu_D(x)$$

c) Commutativity

$$t\big(\mu_A(x),\ \mu_B(x)\big) =\ t\big(\mu_B(x),\ \mu_A(x)\big)$$

d) Associativity

$$t\big(\mu_A(x), t(\mu_B(x), \mu_C(x))\big) = t(t(\mu_A(x), \mu_B(x)), \mu_C(x))$$

- Fuzzy union or (s-norms)

The union of two fuzzy sets A and B is defined as:

$$C = A \cup B$$

The fuzzy operator that can be used to represent the union operation is called triangular conforms (s-norms).

$$\mu_{A\cup B}(x) = S[\mu_A(x), \mu_B(x)]$$

S-norms are two-placed functions s that map from [0, 1] × [0, 1] into [0, 1] that satisfy the following conditions:

a) Boundary conditions

$$s(1,1) = 1; s(\mu_A(x), 0) = s\big(0, \mu_A(x)\big) = \mu_A(x), x \in X$$

b) Monotonicity

$$s\big(\mu_A(x),\ \mu_B(x)\big) \le s\big(\mu_C(x),\ \mu_D(x)\big)$$

$$\text{if} \quad \mu_A(x) \le \mu_C(x) \; and \; \mu_B(x) \le \mu_D(x)$$

c) Commutativity

$$s\big(\mu_A(x),\ \mu_B(x)\big) = s\big(\mu_B(x),\ \mu_A(x)\big)$$

d) Associativity

$$s\big(\mu_A(x), s(\mu_B(x), \mu_C(x))\big) = s(s(\mu_A(x), \mu_B(x)), \mu_C(x))$$

3.2.3 Fuzzy inference systems

Recently, intelligent systems such as artificial neural networks (ANN) and fuzzy systems have undergone remarkable consideration in many areas of medicine, such as breast cancer diagnosis, mortality assessment in intensive care units and diagnostic scoring (Ruiz et al., 2008). Although classical methods (e.g., regression analysis) have been used extensively, they lack the ability of linguistic concept modeling, expert knowledge resembling, and nonlinear input-output mapping. Fuzzy systems, on the other hand, have shown significant ability to solve many types of real-world problems, especially in a system that is complex and difficult to model mathematically, controlled by a human operator or expert, and a system in which ambiguity or vagueness is common (Ivancevic and Ivancevic, 2007). In this study, intelligent prediction systems, called fuzzy inference systems (FIS), are proposed for VO_2 prediction since they have the potential to overcome all limitations that arise due to the presence of ambiguity and vagueness in a VO_2-HR relationship, especially at low workload as well as their applicability at actual work environments.

A fuzzy inference system is a system that uses the concept of fuzzy logic in formulating the mapping from a given input to an output. The inputs and the outputs of the fuzzy system are expressed by variables that range between [0, 1]. Quantization of the inputs and the outputs using linguistic variables, which are basically membership functions defined over the range [0, 1], allows for the consideration of uncertainties associated with some problems where non-fuzzy approaches fail (Ibrahim, 2009). There are three main types of fuzzy inference systems depending on the fuzzy reasoning and the fuzzy IF-THEN rules, namely Mamdani (Mamdani and Assilian 1975), Tsukamoto (Tsukamoto, 1979; Deng, 2002), and Sugeno (Takagi and Sugeno 1985; Sugeno and Kang 1988). This research mainly concerns with Sugeno model, which can be defined as an objective modeling technique that provides a systematic approach for the development of the rule-base from a given input-output dataset (Takagi and Sugeno 1985). The rule-base of this type (n input variables, single output variable, and m rules) takes the following form:

$$IF\ X_1\ is\ A_{11}\ AND\ \dots\ X_j\ is\ A_{1j} \dots AND\ X_n\ is\ A_{1n}\ THEN\ Y = f_1(x_1, \dots, x_j, \dots, x_n)$$
$$\vdots$$
$$IF\ X_1\ is\ A_{i1}\ AND \dots\ X_j\ is\ A_{ij} \dots AND\ X_n\ is\ A_{in}\ THEN\ Y = f_i(x_1, \dots, x_j, \dots, x_n)$$
$$\vdots$$
$$IF\ X_1\ is\ A_{m1}\ AND\ \dots\ X_j\ is\ A_{mj} \dots AND\ X_n\ is\ A_{mn}\ THEN\ Y = f_m(x_1, \dots, x_j, \dots, x_n)$$

where X_j (j=1, 2, ..., n) are the input variables, Y is the output variable, A_{ij} are the fuzzy sets of the input variable j associated with the rule i (for i=1, 2, ..., m), and f_i (x_1, ..., x_j, ..., x_n) are crisp functions that describe the output associated with the rule i. These functions can be any polynomial function of the input variables that can adequately describe the output of the model within the fuzzy region, specified by the antecedent of the rule (Deng, 2002). If these functions are first order polynomials then we call the inference system a first-order Sugeno model, whereas if the crisp functions are second order polynomials, then the inference system is called a second-order Sugeno model. A zero-order Sugeno model refers to a fuzzy inference system with constant crisp functions. A typical fuzzy inference system consists of the following components (Figure 3-4):

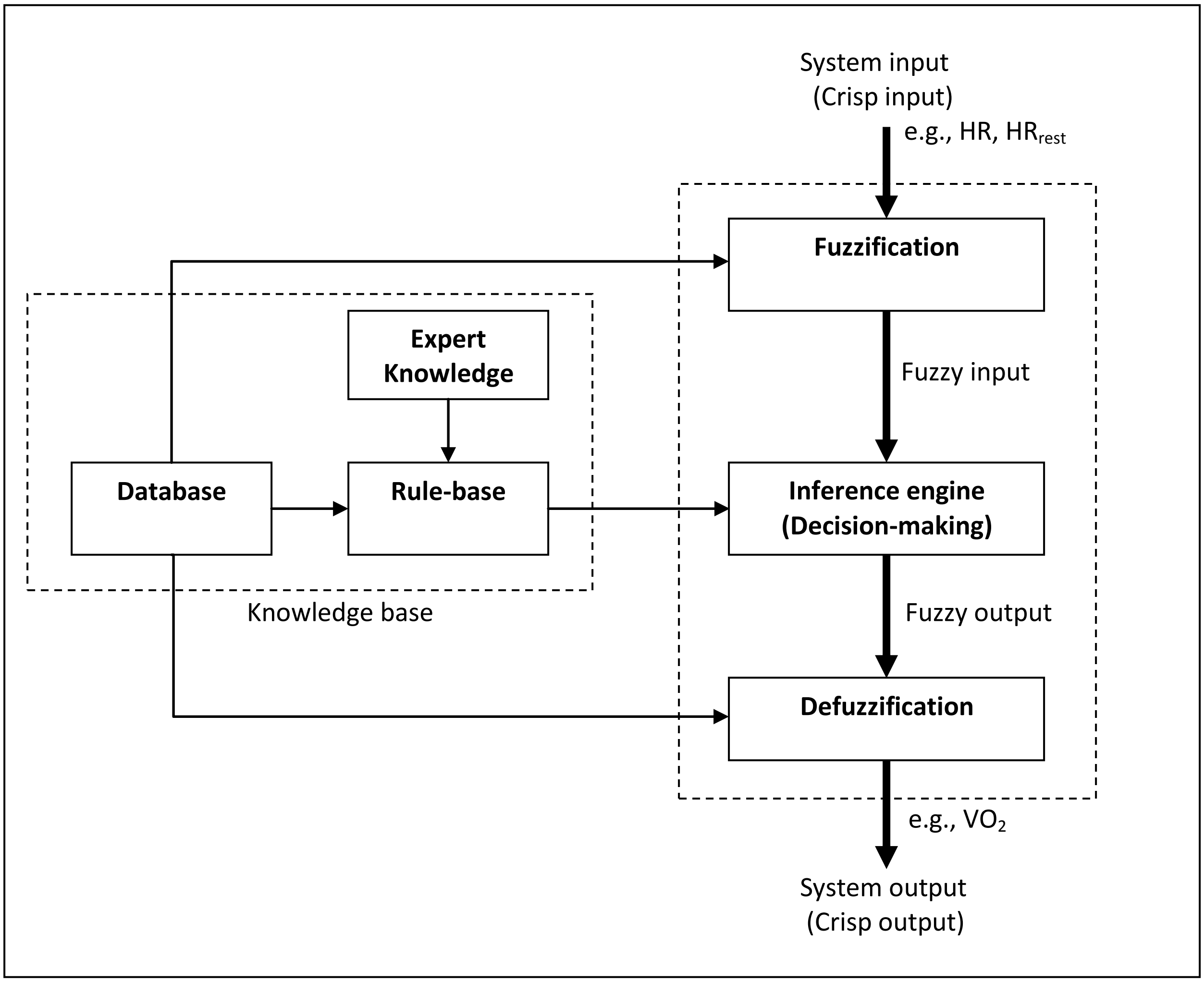

Figure 3-4: Basic structure of the fuzzy inference system

- **Fuzzification interface**

Fuzzification is the process of transforming any crisp value to a corresponding linguistic variable (fuzzy value) based on the appropriate membership function (Ibrahim, 2009). For example, let *X* represents the input variable *Age* and *A* represents the fuzzy set of old people which is described using the triangular membership function $\mu(x)$. Figure 3-5 explains the fuzzification process of the crisp input value (x = 60 years) into a fuzzy value μ (60) = 0.5.

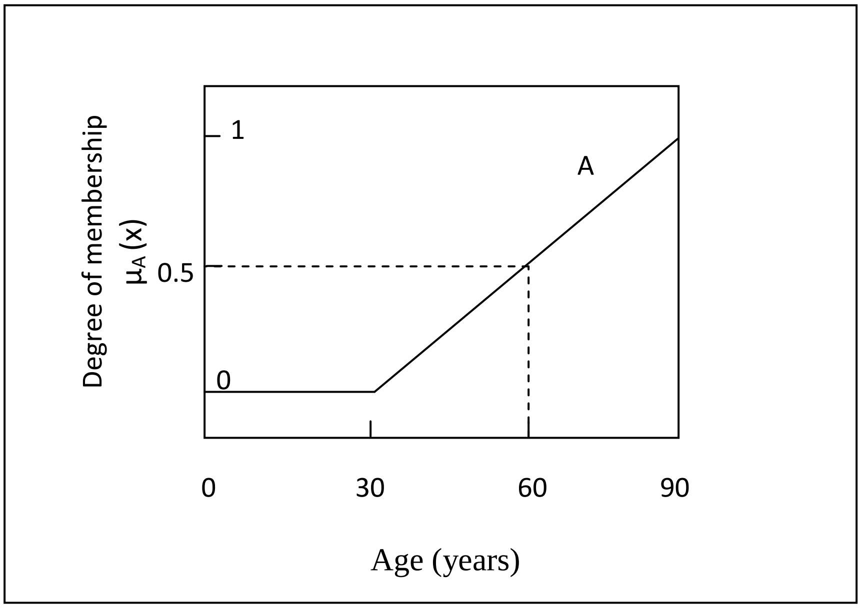

Figure 3-5: Input fuzzification

- **Knowledge base**

The knowledge (rule) base unit contains membership function definitions and the IF-THEN rules. This unit is considered the heart of the FIS because it explains the relationship between inputs (e.g., heart rate, ventilation rate, age, gender etc.) and output (e.g., VO_2) in order to assist in predicting the amount of oxygen consumed by workers. There are two main approaches used to construct the rule-base, subjective and objective. In subjective fuzzy system modeling, the rule-base is solicited from experts in an attempt to model the reasoning process of an expert. To the contrary, objective fuzzy system modeling uses (input-output) data obtained from an actual system (e.g., measurements collected during actual work) to construct the rule-base. For more information on this, refer to (Sugeno and Kang 1988). In many situations, it is more appropriate to develop an objective fuzzy system model from the input and output data of the system, especially when it is possible to obtain the data from a precise mathematical model or from the actual system itself. In this dissertation, objective fuzzy system modeling will be used to model the relationship between oxygen consumption and various inputs, such as heart rate and ventilation rate. Accordingly, different experiments will be conducted to collect the required data for this purpose.

As previously mentioned, the rule-base development can be achieved either subjectively (based on expert's opinions) or objectively (based on input-output data). An intuitive method used for objective rule generation is known as a clustering algorithm. This involves grouping data into similarly behaving clusters and evaluating the system behaviour of these clusters such that each cluster represents both a group of associated data in a data space, and also a rule in the knowledge base of the system (Demirli and Muthukumaran, 2000).

Several different clustering algorithms exist, however, due to its capability and efficiency in automatic rule generation, the subtractive clustering algorithm will be implemented in this dissertation (Chiu, 1996; Emami et al., 1998; Demirli and Muthukumaran, 2000). The subtractive clustering method assumes each data point is a potential cluster center and calculates a measure of the likelihood of whether each data point could define the cluster center, based on the potential of surrounding data points. Using this method, the quantity of calculation is in direct proportion to the number of data points rather than dimensions. Let us consider m dimensions and n data points ($x_1, x_2, \ldots, x_n$). More generally, we assume that these data points have fallen into a unit hyper box. Because each data point is a candidate cluster center, the potential of a data point x_i is defined as:

$$\boldsymbol{P_i} = \sum_{\boldsymbol{j}=1}^{\boldsymbol{n}} \boldsymbol{e}^{-\alpha \|\boldsymbol{x_i} - \boldsymbol{x_j}\|^2} \qquad \forall \boldsymbol{i} \qquad (3.4)$$

where, $\alpha = \dfrac{\gamma}{\boldsymbol{r_a}^2}$

r_a is a positive number which represents the cluster radius that defines an adjacent area, such that a data point has the highest potential if it is surrounded by more data points with the radius r_a. After calculating the potential of each data point, we can select the data point with the highest potential to be the first cluster center. Assume that x_{c1} is selected and P_{c1} is its potential, the potential of each data point x_i can be revised by the following formula:

$$\boldsymbol{P_i} = \boldsymbol{P_i} - \boldsymbol{P_{c1}} \boldsymbol{e}^{-\beta \|\boldsymbol{x_i} - \boldsymbol{x_{c1}}\|^2} \qquad \forall \boldsymbol{i} \qquad (3.5)$$

where, $\beta = \dfrac{\gamma}{\boldsymbol{r_b}^2}$

and $\boldsymbol{r_b} = \eta * \boldsymbol{r_a}$

Obviously, the density of data points that are close to the first cluster center will markedly reduce, so that these data points cannot become the next cluster center. r_b defines an adjacent area where the function of the potential of a data point will markedly reduce. This is called the penalty radius and it is usually greater than the cluster radius (r_b > r_a). In order to prevent the cluster centers from appearing next to each other, commonly expressed to let r_b = 1.5 r_a. η is called the squash factor. Once the potential of data points is modified, the data point with the highest potential is selected to be the next cluster center. Then the potential of all data points can again be continuously modified by repeating this process until the appointed number of cluster centers is obtained or ascertained automatically based on determinate conditions.

- **Inference engine**

The inference engine is a simulation of the human decision making process. Principally, it consists of two processes: the implication and the aggregation processes. The implication process reshapes the consequent fuzzy set by a single number provided by the antecedent. The most popular implication methods are the minimum or the intersection operator (t-norm) which truncates the output fuzzy set. The aggregation process, however, is the process in which the output fuzzy sets of all rules are combined into a single fuzzy set. Different aggregation operators exist and they can be any union operator (s-norms).

- **Defuzzification interface**

The defuzzification interface converts the fuzzy value of the output to a single real number or crisp value back again. Different defuzzification methods exist, however, the most commonly used method is known as the center of gravity (COG), which was developed by Sugeno (1985). Using the COG method, the crisp output value corresponds to the center of the area divided by the aggregated membership function of output fuzzy sets. Therefore, the defuzzified value is equal to:

$$y = \frac{\int x.\mu_{out}(x)dx}{\int \mu_{out}(x)dx} \qquad (3.6)$$

where y is the defuzzified (crisp) output, x is the universe of discourse, and μ_{out} is the aggregated resultant membership function of the output fuzzy set.

3.2.4 Fuzzy modeling

Fuzzy modeling is concerned with describing the behaviour of a system by using a fuzzy model or a fuzzy inference system. Fuzzy modeling involves two main consecutive phases: structure and parameter identifications.

The structure identification concerns the development of an initial fuzzy inference system that uses the fuzzy set theory to formulate the map from any given input to an output. According to Jang et al. (1997), Deng (2002) and Kaya et al. (2003), this phase includes four main steps to select relevant (significant) input variables, select the appropriate type of fuzzy model, determine the rule-base, and determine the membership functions. The parameter identification phase, on the other hand, relates to the optimal adjustment of the initial fuzzy inference system's parameters to best fit the input-output data set. This involves two main steps: selecting the appropriate parameters of membership functions and optimizing the antecedent's and the consequent's parameters using optimization techniques.

3.3 Artificial neural networks

An artificial neural network is a computational model that mimics, at a simple level, the human brain's ability for parallel information processing (George and Cardullo, 1999; Saggio et al., 2009). The ANN consists of a large number of independent and interconnected processing units called "neurons". The neurons communicate (work) with each other by weighted connections so that they can solve specific problems.

3.3.1 Neural networks structure

Generally, there are three categories of ANN (feed-forward, feed-back and self-organized) such that each model with its unique properties and advantages is suitable for a specific application (Ruiz et al., 2008). The early 1960s witnessed the development of the simplest form of feed-forward ANN, known as "Perceptron" (Rosenblatt, 1962). However, ANN gained rapid popularity in the 1980s with the development of the multi-layered perceptron (Rumelhart et al., 1986; Lippmann, 1987; Widrow and Lehr, 1990; Karayiannis and Venetsanopoulos, 1993).

The multilayer feed-forward ANN, also called multilayer perceptron (MLP), is one of the most commonly and successfully used ANN in applications (Ghalia and Alouani, 1995; Tareghian and Kashefipour, 2007; Ruiz et al., 2008). It is composed of an input layer (includes source nodes), one or more hidden layers (these include computation nodes), and an output layer (includes computation nodes). This is a feed-forward ANN because the input signal moves through the network on a layer-by-layer basis only in a forward direction. It does not move in lateral or backward directions. In this structure, neurons of adjacent layers are connected by sets of synaptic weights and the output of each layer feeds the neurons of the next layer (Karayiannis and Venetsanopoulos, 1993). Studies have proven the efficiency of ANN with one hidden layer in most applications (Cybenko, 1989; Funahashi, 1989; Hornik et al., 1989; Malek et al., 2010). Figure 3-6 shows a three-layered feed-forward ANN with n inputs, m neurons in the hidden layer and a single output.

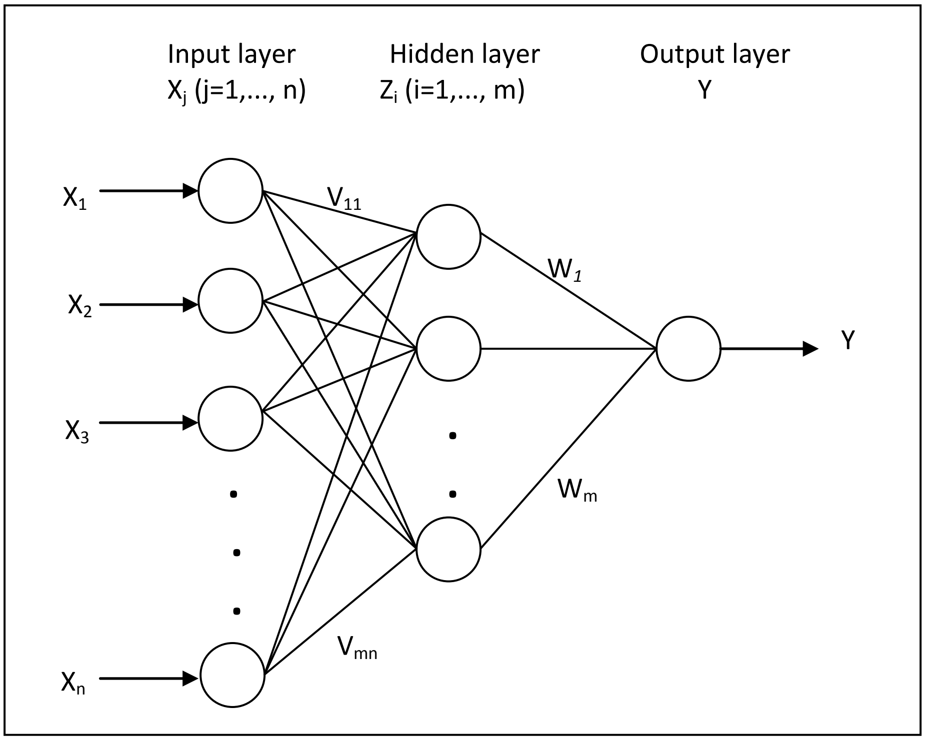

Figure 3-6: Feed-forward ANN with one hidden layer and a single output

Figure 3-7 illustrates the mathematical representation within the artificial neurons, which are considered the basic elements of ANN. Artificial neurons can process multiple input signals by applying an activation function on the linear combination of the input signals, as shown in equations (3.7 and 3.8).

$$V = \sum_{j=1}^{n} W_j X_j \tag{3.7}$$

$$Y = \varphi\left(\sum_{j=1}^{n} W_j X_j + W_0\right) \tag{3.8}$$

where X_j is the input signal applied to neuron the neuron under consideration, W_j represents the synaptic weight connecting the input signal j to the neuron under consideration, W_0 is a bias, and $\varphi(.)$ is the activation function which is usually non linear (e.g., logistic and hyperbolic tangent functions). Furthermore, the bias can be considered as a synaptic weight connecting an input signal of +1 to the neuron under consideration, and thus equation (3.8) can be expressed as follows:

$$Y = \varphi\left(\sum_{j=0}^{n} W_j X_j\right) \qquad (3.9)$$

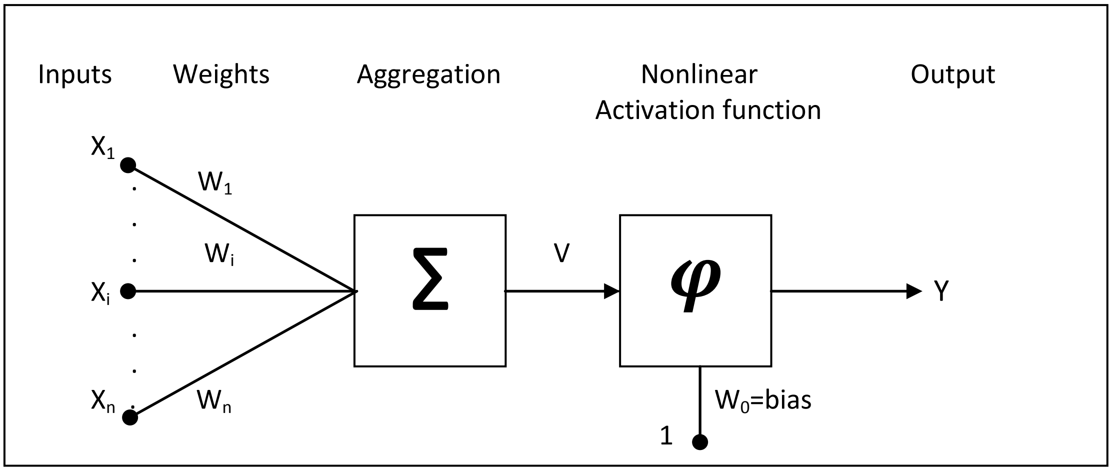

Figure 3-7: Artificial neuron's structure

3.3.2 Neural networks learning algorithm

In addition to the structure of ANN, it is important to determine the learning process for ANN where all the synaptic weights are adjusted (optimized) according to a given criteria. This learning capability of ANN is one of its key strengths. According to the type of learning process, ANN can be classified into one of the following networks: networks with supervised learning and networks with unsupervised learning. The former network requires a teacher to learn the desired output, while in the latter networks internal models are designed to capture regularities in input space (Vemuri, 1988; George and Cardullo, 1999; Deng, 2002). This section focuses on the supervised learning algorithm because it is the learning method used in this dissertation.

In supervised learning, the network learns the relationship between inputs and outputs based on a training data set so as to provide a network that is efficiently capable of performing input-output mappings for new samples. Given the desired input-output data set, the adjustable parameters (weights) of the network can be updated by using a learning rule. The most commonly used supervised learning method with multi-layered neural networks is the back-propagation method (Rumelhart and McClelland, 1987; Ghalia and Alouani, 1995).

According to Haykin (1994), the back-propagation learning algorithm consists of two phases (passes): forward and backward. In the forward pass, the input signal propagates forward through the network, starting from the source nodes and moving forward towards the hidden layers until it reaches the output layer where a set of outputs (actual response) is obtained. A departing signal from a node is represented as a function of all inputs and their associated weights applied to that node, and therefore input signals are also called function signals (Haykin, 1994). The function signal produced at the output of neuron *i* (also called the input signal of neuron *j*) is defined and calculated as:

$$y_j(n) = \varphi\left(v_j(n)\right) \qquad (3.10)$$

where *n* is the training pattern (input data) presented to the network, and $\varphi(.)$ is the activation function describing the nonlinearity of input-output mapping associated with neuron *j*. $v_j(n)$ is the weighted sum of all inputs plus bias of neuron *j* and it is given as:

$$v_j(n) = \sum_{i=0}^{m} w_{ji}(n).y_i(n) \qquad (3.11)$$

where *m* is the inputs to neuron *j*, $w_{ji}(n)$ is the synaptic weight that characterizes the connection from neuron *i* to neuron *j*, and $y_i(n)$ is the is the input signal of neuron *i*. When the signal reaches the output layer (e.g., neuron j belongs to the output layer), then the error signal at the output of neuron *j* is calculated as:

$$e_j(n) = d_j(n) - y_j(n) \qquad (3.12)$$

where $d_j(n)$ refers to the desired response for neuron *j*. The forward pass ends at the output layer by computing the error signal for each neuron belonging to this layer.

On the other hand, the backward pass begins at the output layer by propagating the error signals backward layer-by-layer through the network. During the back propagation of the error signals, the synaptic weights of the network are adjusted to reduce the difference between the desired and the actual responses. This is achieved by the recursive computation of what is referred to as the local gradient (δ) for each neuron according to the delta rule expressed in equation (3.13).

$$\Delta w_{ji}(n) = \eta.\delta_j(n).y_i(n) \qquad (3.13)$$

where $\Delta w_{ji}(n)$ is the correction applied to the synaptic weight $w_{ji}(n)$ and η is called the learning-rate parameter of the back-propagation algorithm. The computation of the local gradient $\delta_j(n)$ depends on the location of neuron *j*. If neuron *j* belongs to the output layer, the local gradient is equal to the error signal of neuron *j* multiplied by the first derivative of the activation function (used to describe the nonlinearity) associated with neuron *j* (Figure 3-8). This can be expressed as:

$$\delta_j(n) = e_j(n)\varphi_j'\big(v_j(n)\big) \qquad (3.14)$$

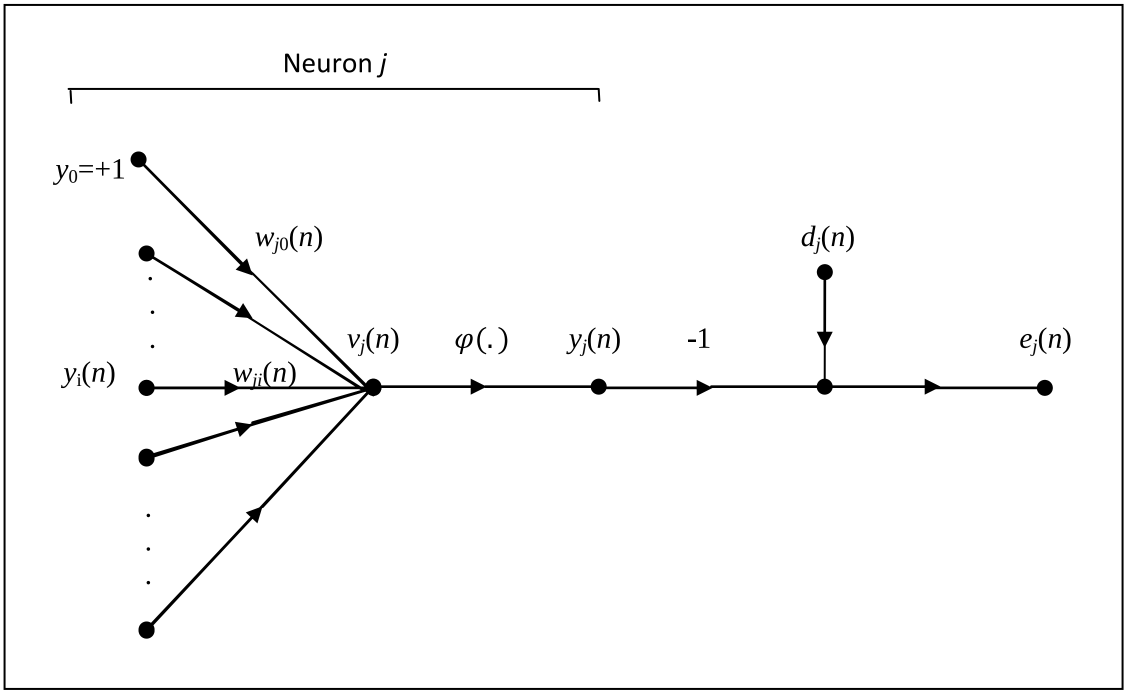

Figure 3-8: Signal flow associated with neuron *j*, adapted from Haykin (1994)

Consequently, determining $\delta_j(n)$ for the output node *j* will allow for the adjustment of the weights of all connections feeding into neuron *j*. After calculating the local gradients of all output nodes, the local gradients for all nodes in the hidden layer preceding the output layer is calculated using the following equation:

$$\delta_j(n) = \varphi_j'\big(v_j(n)\big)\textstyle\sum_k \delta_k(n).w_{kj}(n) \qquad (3.15)$$

where in this case neuron *j* belongs to a hidden layer, see Figure 3-9. The summation part over *k* neurons depends on two set of terms. The first set of terms, $\delta_k(n)$, depends on the error signals $e_k(n)$ for all neurons that are to the immediate right of the hidden neuron *j* and are directly connected to neuron *j*. The second set of terms, $w_{kj}(n)$, depends on the synaptic weights of all connections from the hidden neuron *j* to all the neurons that are to the immediate right of neuron *j*.

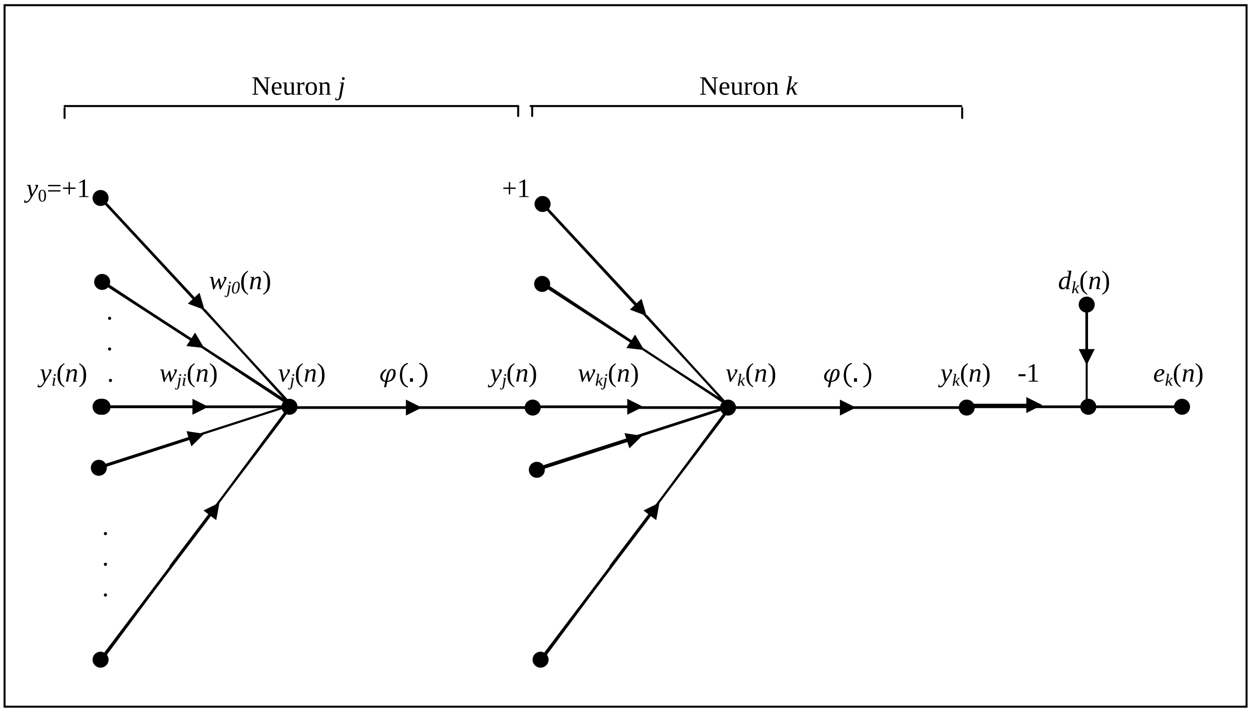

Figure 3-9: Signal flow associated with the output neuron k and the hidden neuron *j*, adapted from Haykin (1994)

3.4 Neuro-fuzzy systems

Nowadays, there is an urgent need for intelligent systems that mimic human ways of thinking to make decisions to solve real-world problems. In 1990, Hayashi and Imura showed that any fuzzy inference system could be approximated by a feed-forward ANN and vice versa. Since then, the fusion of fuzzy inference systems and artificial neural networks has attracted attention in the research of different fields and applications (Hayashi and Imura, 1990; Carpenter et al., 1992; Gupta, 1992; Buckley and Hayashi, 1993; Halgamuge and Glesner, 1994; Arao et al., 1995; Brown et al., 1995; Lin and Lee, 1996; Bunke and Kandel, 2000; Fuller, 2000; Mitra and Hayashi, 2000; Abraham, 2005). The main strength of this fusion is due to the fact that the two paradigms work together to complement each other, rather than to compete with each other. On one hand, the FIS provides a computational framework that takes into consideration the uncertainty and imprecision of data as well as interpretability of consequent decisions. Such a computational framework is considered an advantage for ANN. On the other hand, ANN has the ability to learn and adapt to changes, which is considered an advantage for FIS. Reviewing the literature reveals several works concerned with the fusion of FIS and ANN, such as Lin and Lee (1991), Khan and Venkatapuram (1993), Hollatz (1995), Nauck and Kruse (1999) and Pal and Mitra (1999), Souza et al. (2001), Abraham (2001, 2002), Abraham and Khan (2003) (Abraham, 2005).

3.4.1 Types of neuro-fuzzy systems

There are different ways to combine FIS and ANN where all forms of combinations are called neuro-fuzzy systems. According to Nauck et al. (1997), Vieira et al. (2004) and Abraham (2005), all forms of fusion between FIS and ANN are considered within three categories: cooperative, concurrent and integrated (hybrid) neuro-fuzzy systems.

- In cooperative neuro-fuzzy systems, both FIS and ANN are employed independently where the latter is only used as an initial phase to determine the FIS's membership functions or fuzzy rules through the learning process from the training data, see Figure 3-10. Once the initial phase is completed, ANN is no longer used and the FIS is in effect. Several examples of cooperative neuro-fuzzy systems cited by Abraham (2005) include: fuzzy associate memories (Kosko, 1992), fuzzy rule extraction using self organizing maps (Pedrycz and Card, 1992), and the systems capable of learning of fuzzy set parameters (Nomura et al., 1992).

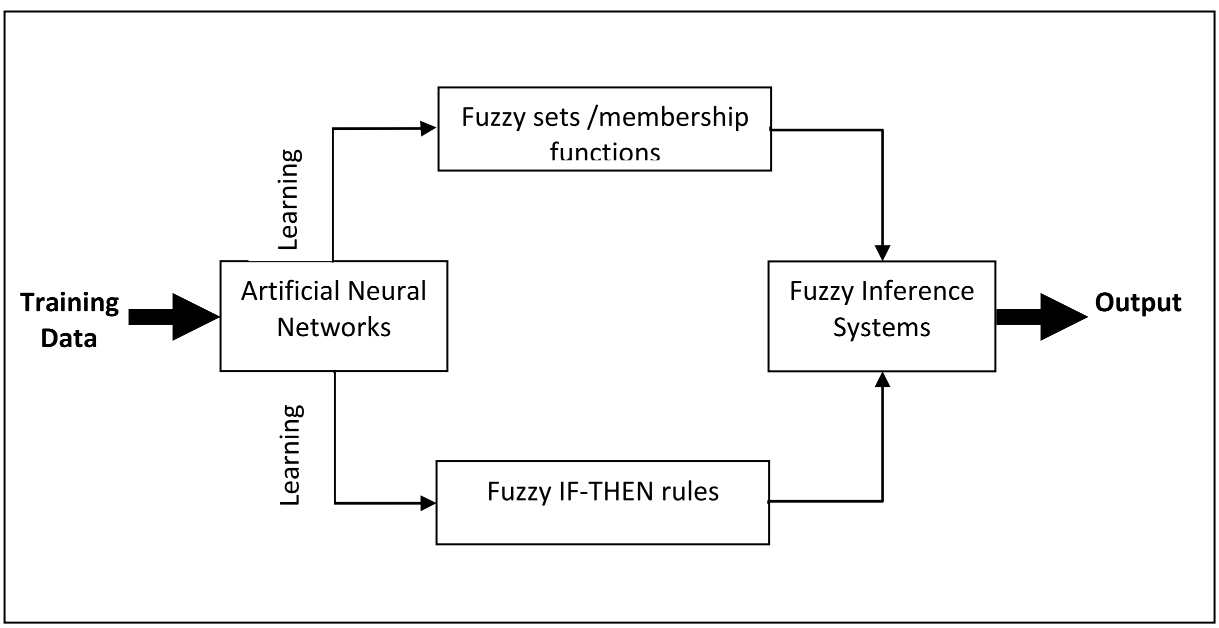

Figure 3-10: Cooperative neuro-fuzzy systems

- In concurrent neuro-fuzzy systems, ANN assists FIS continuously (as required) but not only in the initial phase, as is the case in cooperative systems. Moreover, the fusion between ANN and FIS in the concurrent neuro-fuzzy systems is independent and similar to the cooperative systems. For instance, in some situations where inputs cannot be measured directly from the process, ANN acts as a pre-processor to the inputs to determine the required parameters (e.g., fuzzy sets and fuzzy rules). In other situations ANN acts as a post-processor to the fuzzy outputs to provide outputs that are applicable to the process (Vieira et al., 2004; Abraham, 2005). In concurrent neuro-fuzzy systems, the use of ANN as a pre-processor and/or post-processor is to improve the overall performance of FIS. Figure 3-11 shows an example of concurrent neuro-fuzzy systems.

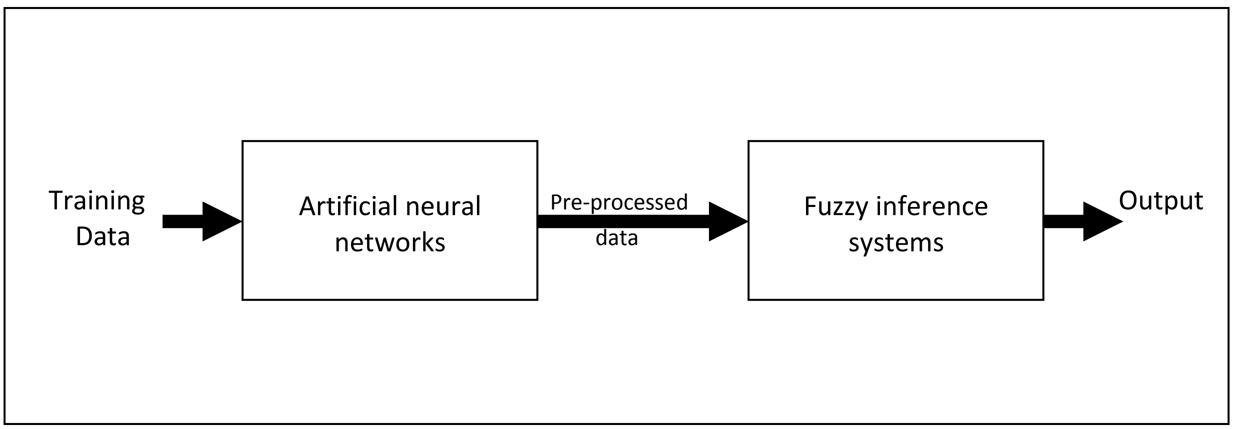

Figure 3-11: Concurrent neuro-fuzzy systems

- In integrated neuro-fuzzy systems, there is a synergy between FIS and ANN unlike the cooperative and concurrent systems, which use the two paradigms independently. The integrated neuro-fuzzy systems, also known as hybrid neuro-fuzzy systems, can be described as a fuzzy system that uses the learning mechanism provided by ANN to determine its parameters (e.g., fuzzy membership functions and fuzzy rules) (Nauck et al., 1997; Vieira et al., 2004). Therefore, the fuzzy system is represented by a special ANN-like framework to facilitate the implementation of the learning mechanism. The Takagi-Sugeno hybrid neuro-fuzzy systems implement a combination of least squares method (to determine the parameters of linear combinations in the consequent part of the rules) and the back-propagation learning algorithm (to learn the parameters of the membership functions of in the rule’s antecedent) (Figure 3-12).

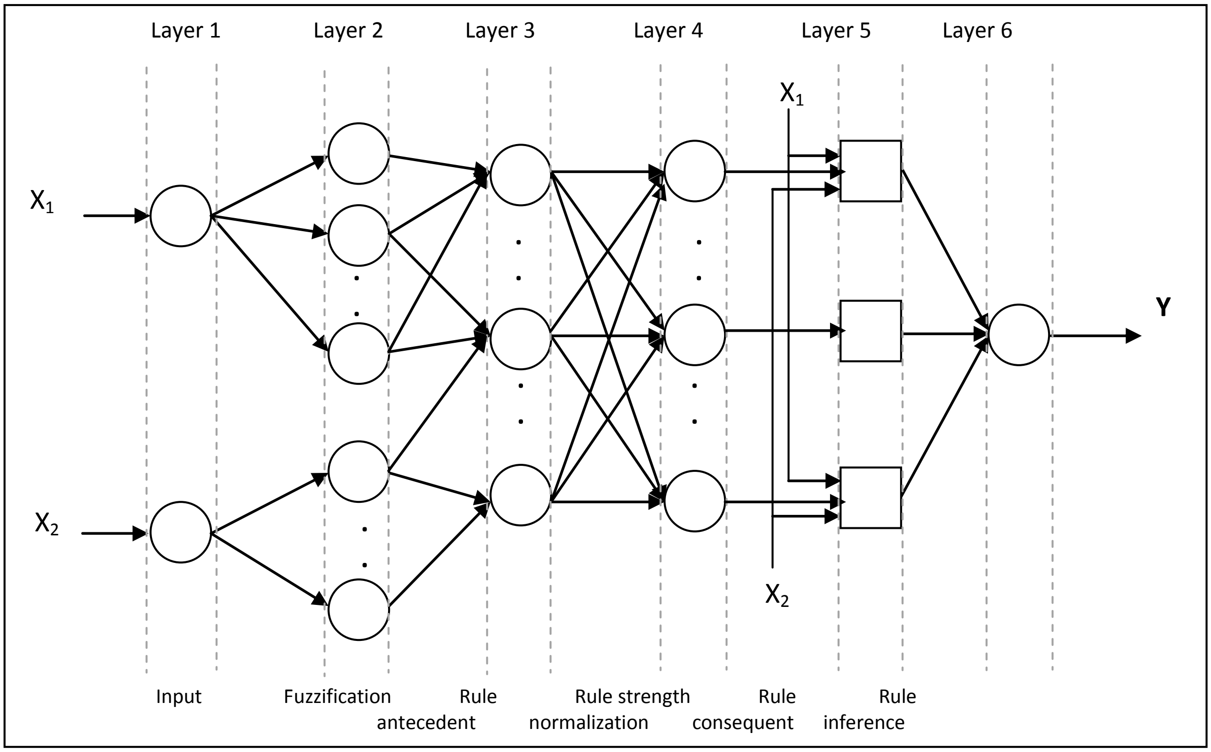

Figure 3-12: Tagaki-Sugeno hybrid neuro-fuzzy system, adapted from Abraham (2005)

Examples of integrated neuro-fuzzy systems implementing Mamdani FIS include: fuzzy adaptive learning control network (FALCON) (Lin and Lee, 1991), neuronal fuzzy controller (NEFCON) (Nauck and Kurse, 1997) and neuro-fuzzy function approximation (NEFPROX) (Nauck and Kruse, 1999). Examples of integrated neuro-fuzzy systems implementing Takagi-Sugeno FIS include: adaptive neuro-fuzzy inference system (ANFIS) (Jang, 1992), self constructing neural fuzzy inference network (SONFIN) (Feng and Teng, 1998) and dynamic evolving fuzzy neural network (dmEFuNN) (Kasabov and Qun, 1999). The following sections focus on one of the earliest and most commonly used hybrid neuro-fuzzy systems (ANFIS) as it is used throughout the dissertation.

3.4.2 Adaptive neuro-fuzzy inference systems structure

The ANFIS can be described as a fuzzy Sugeno model considered within the framework of an adaptive system (6-layer feed-forward ANN) to facilitate learning and adaptation (Jang, 1993; Güler and Übeyli, 2004, 2005; Yildiz et al., 2009). This adaptive framework makes the ANFIS modeling more systematic, less reliant on expert knowledge and does not require defuzzification process and hence it is commonly used in objective nonlinear fuzzy modeling

(Deng, 2002; Ylidiz et al., 2009). The architecture of ANFIS can be best described by the following Sugeno type (first order) fuzzy model, which consists of two fuzzy IF-THEN rules with two inputs and a single output:

$$Rule\ 1{:}\ IF\ x\ is\ A_1\ AND\ y\ is\ B_1 THEN\ f_1(x,y) = p_1x + q_1y + r_1$$

$$Rule\ 2{:}\ IF\ x\ is\ A_2\ AND\ y\ is\ B_2\ THEN\ f_2(x,y) = p_2x + q_2y + r_2$$

where x and y are inputs variables, A_i and B_i (i =1, 2) are the fuzzy sets associated with inputs x and y, respectively. $f_i(x,y)$ (for i = 1, 2) are the outputs (linear combination of input variables) within the fuzzy region specified by rule i, p_i and q_i are the design parameters associated with rule i which are determined during the learning process. The ANFIS representation of these two rules consists of six layers in which a circle indicates a fixed node and a square indicates an adaptive node (Figure 3-13). According to Güler and Übeyli, (2004), Abraham (2005), Buragohain and Mahanta (2008) and Yildiz et al. (2009), the functionality of each layer is described as follows:

- Layer 1: which is also called the input layer does not involve any computations. Each input variable is applied to an input node through which it moves to the first hidden layer.
- Layer 2: (also known as the fuzzification layer) includes adaptive nodes in which each generates membership grades of an input variable. The outputs of the nodes belonging to this layer (O_i^1) are given by:

$$O_i^2 = w_i = \mu_{A_i}(x) \qquad i = 1,2$$

$$O_i^2 = w_i = \mu_{B_{i-2}}(y) \qquad i = 3,4$$

  The membership functions can be any continuous, piecewise differentiable functions (e.g., Gaussian, generalized bell shaped and triangular). Assuming a Gaussian membership function, the output of the node (O_i^2) can be computed as:

$$\mu_{A_i}(x) = e^{-\frac{1}{2}\left(\frac{x-c_i}{\sigma_i}\right)^2} \qquad i = 1,2$$

$$\mu_{B_{i-2}}(y) = e^{-\frac{1}{2}\left(\frac{y-c_i}{\sigma_i}\right)^2} \qquad i = 3,4$$

  where $c_i\ and\ \sigma_i$ are the parameters (centers and widths respectively) of the Gaussian membership functions characterizing the fuzzy sets describing each input variable.
- Layer 3: (also known as rule antecedent layer) includes fixed nodes in which each node represents the antecedent part of the associated rule. Each node uses the product t-norm

operator to calculate the firing strength w_i of the associated rule. As a result, the output of each node is given as:

$$O_i^3 = w_i = \mu_{A_i}(x).\mu_{B_i}(y), \qquad i = 1, 2$$

- Layer 4: (also known as rule strength normalization layer) includes fixed nodes in which each plays a normalization role to the firing strength obtained from the previous layer. Essentially, each node calculates the ratio of the corresponding rule's firing strength to the sum of all rules firing strength. As a result, the output (normalized firing strength) of each node in this layer is given as:

$$O_i^4 = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \qquad i = 1,2$$

- Layer 5: (also called rule consequent layer) includes adaptive nodes in which each is represented by a node function that is described as the product of the normalized firing strength (obtained from layer 4) and a first order polynomial:

$$O_i^5 = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \qquad i = 1, 2$$

- Layer 6: (also known as rule inference layer) includes a single fixed node that calculates the overall output as follows:

$$O_i^6 = \sum_{i=1}^{2} \overline{w}_i f_i = \frac{\sum_{i=1}^{2} w_i f_i}{\sum_{i=1}^{2} w_i}$$

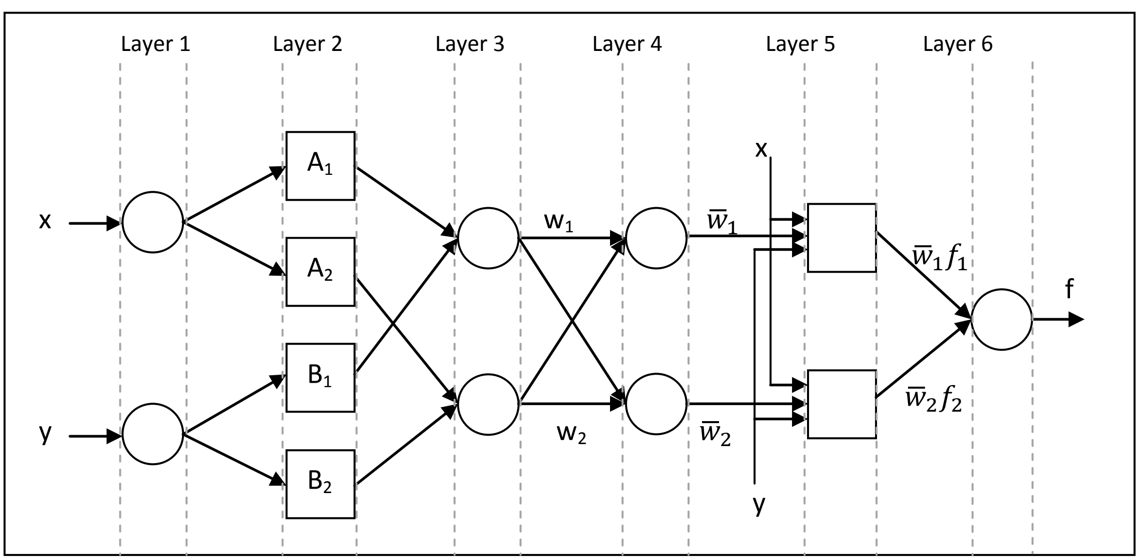

Figure 3-13: The architecture of ANFIS with 2 inputs and a single output

The preceding ANFIS architecture includes two adaptive layers, namely, layer 2 and layer 5. In layer 2, there are eight modifiable parameters$\{c_i \ and \ \sigma_i: i = 1, 2, 3, 4\}$. These parameters are associated with the input membership functions called, "premise or antecedent parameters". In layer 5, there are also six modifiable parameters$\{p_i, q_i \ and \ r_i: i = 1, 2\}$. These parameters are associated with the first order polynomial called, "consequent parameters". In ANFIS, both sets of modifiable parameters (premise and consequent parameters) are considered for optimization.

3.4.3 Adaptive neuro-fuzzy inference systems learning mechanism

The purpose of the learning algorithm is to learn or tune all the modifiable parameters from the input-output training data, such that ANFIS is capable of making inferences given new input sets. Using the conventional gradient descent method in conjunction with error back-propagation process for neural network learning is a time consuming optimization problem (Deng, 2002). Therefore, it was necessary to modify the learning algorithm to fit the neuro-fuzzy architecture. In 1997, Jang and colleagues developed a hybrid learning algorithm for fast ANFIS parameters identification. The hybrid learning algorithm consists of two passes: a forward pass and a backward pass. In the forward pass, the least squares method is used to optimize the consequent parameters (these are linear parameters) with the premise parameters being fixed. The backward pass begins immediately after the optimal consequent parameters have been determined wherein the (back-propagation) gradient descent method is used to optimally adjust the premise parameters. The output of ANFIS is thus determined using the consequent parameters found in the forward pass, while output error is used to adjust the premise parameters using the back-propagation algorithm. This process is then repeated until a predefined error is reached. Studies have shown that this hybrid learning algorithm is highly efficient in training ANFIS especially for nonlinear modeling (Jang, 1993; Güler and Übeyli, 2004; Yildiz et al., 2009).

CHAPTER 4: ARTICLE 1 - ESTIMATING OXYGEN CONSUMPTION FROM HEART RATE USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM AND ANALYTICAL APPROACHES

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4.1 Abstract

In new approaches based on adaptive neuro-fuzzy systems (ANFIS) and analytical method, heart rate (HR) measurements were used to estimate oxygen consumption (VO_2). Thirty-five participants performed Meyer and Flenghi's step-test (eight of which performed regeneration release work), during which heart rate and oxygen consumption were measured. Two individualized models and a General ANFIS model that does not require individual calibration were developed. Results indicated the superior precision achieved with individualized ANFIS modeling (RMSE= 1.0 and 2.8 ml/kg.min in laboratory and field, respectively). The analytical model outperformed the traditional linear calibration and Flex-HR methods with field data. The General ANFIS model's estimates of VO_2 were not significantly different from actual field VO_2 measurements (RMSE= 3.5 ml/kg.min). With its ease of use and low implementation cost, the General ANFIS model shows potential to replace any of the traditional individualized methods for VO_2 estimation from HR data collected in the field.

Keywords: work design; oxygen consumption; heart rate monitoring

4.2 Introduction

Ergonomics and occupational health and safety researchers have demonstrated the importance of designing jobs within the physiological capacity of the workforce (Dempsey et al., 2008). Studies have shown that designing jobs based on the balance between this capacity and the energetic demands of physical jobs is key to maintaining workforce safety and productivity (Malchaire et al., 1984; Abdelhamid, 1999; Wu and Wang, 2002; Dempsey et al., 2008). Oxygen consumption (VO_2) reflects energy expenditure (EE) associated with physically demanding jobs (Malchaire et al., 1984; Smolander et al., 2008; Wu and Wang, 2002; Bouchard and Trudeau, 2008). Since direct measurement of VO_2 requires sophisticated and costly devices, is invasive and often not practical in actual work environments, attempts have been made to find alternative feasible estimation methods (e.g., ISO-8996, 2004; Smolander et al., 2008). Many researchers have reported a linear relationship between oxygen consumption and heart rate for a wide variety of activities (Wyndham et al., 1962; Poulsen and Asmussen, 1962; McArdle et al., 1971; Rodahl et al., 1974; Evans et al., 1983; Gordon et al., 1983; Astrand and Rodahl, 1986). Hence, determining an individual's VO_2-HR relationship (calibration curve) has become a very common practice to assess VO_2 from HR data (Smolander et al., 2008). This calibration process involves measuring an individual's HR and VO_2 while performing a graded exercise, such as treadmill, stationary bicycle or step-test. The linear relationship between the two variables is then modeled using graphical or linear regression analysis. The model is then used to estimate VO_2 from HR data collected in the field for the same individual.

One major criticism of this method is the difficulty of establishing individual calibration curves at workplaces with large working populations. Even though the calibration procedure is simple, it is time consuming (at least 45 minutes per individual), requires a trained practitioner, and requires access to a controlled environment. Another criticism is the fact that at low activity levels (low workload intensity), the relationship between HR and VO_2 is nonlinear and often deviates from the calibration curve and thus may produce inaccurate estimates of VO_2 (Abdelhamid, 1999; Bouchard and Trudeau, 2008; Smolander et al., 2008). In recent years, a number of artificial intelligence (AI) techniques have been proposed as alternatives to conventional statistical methods (Jang et al., 1997; Kaya et al., 2003; Yildirim and Bayramoglu, 2006). One of the most effective AI techniques, particularly for function approximation and pattern recognition, is the adaptive neuro-fuzzy inference system (ANFIS). It combines the unique ability of fuzzy logic to make decisions in uncertain conditions with the learning and adaptive capabilities of artificial neural networks (Kaya et al., 2003). ANFIS has consistently been demonstrated effective in solving nonlinear function approximation problems, particularly in biomedical engineering (Güler and Übeyli, 2004, 2005; Übeyli and Güler, 2005a, 2005b).

The primary objective of the present study is to develop a fuzzy-based general model for VO_2 estimation from HR that does not require individual calibration and hence can be used quickly and easily by practitioners in actual workplaces. The secondary objective is to develop individualized models based on fuzzy logic and analytical methods that provide higher accuracy VO_2 estimates for laboratory and small population work environments applications. The proposed models are expected to improve handling of the nonlinearity and uncertainty involved in VO_2 estimation. Heart rate and VO_2 measurements performed in a laboratory environment and in the field were used to develop and test the proposed models. Their performance was compared with traditional individual methods, namely linear calibration (Schulz et al., 1989; Bouchard and Trudeau, 2008) and Flex-HR (Spurr et al., 1988; Ceesay et al., 1989) methods.

4.3 Methods

A laboratory study was first conducted to develop individualized VO_2 prediction models for each participant and compare their quality of fit performance. Then, part of the laboratory participants' data (approximately 70%) was used to develop the General ANFIS model, and the remaining data were used to feed it to generate VO_2 estimates that could be compared with VO_2 measurements. Next, a field study was conducted to collect new data to test and compare the performance of the different models (General ANFIS and individualized models).

4.3.1 Participants

A total of 27 healthy men aged from 20 to 45 years participated in the laboratory study and eight male forest workers performing regeneration release work participated in the field study (Table 4.1). Participants had to pass the pre-activity readiness questionnaire (PAR-Q) before being accepted for the studies (Chisholm et al., 1975; Shephard, 1988). No participants were competitive athletes, and none regularly used medication. Both studies were approved by the Human Research Ethics Committee of Polytechnique Montréal. All participants signed a written informed consent form prior to partaking in the studies.

Table 4.1: Physical characteristics of the participants

Characteristics	Laboratory (n=27)		Field (n=8)	
	Mean (SD)	**Range**	**Mean (SD)**	**Range**
Age (years)	33.5 (8.7)	[21, 46]	24.0 (2.5)	[20, 28]
Weight (kg)	79.8 (22.3)	[63.6, 104.5]	72.9 (10.7)	[57.3, 100]
Height (cm)	172.6 (2.3)	[165, 185]	175.0 (7.0)	[160, 190]
BMI (kg.m^{-2})	26.9 (2.8)	[21.2, 30.2]	23.9 (2.8)	[20.6, 30.2]
VO_2max (ml.kg^{-1}.min^{-1})	38.7 (5.8)	[30, 45]	46.9 (6.3)	[39.5, 54]
HR (bpm)	96.1 (19)	[49, 157]	106.2 (25.6)	[51.6, 146.7]
HR_{rest} (bpm)	79.2 (10.6)	[53.7, 96.1]	66.3 (10.3)	[55.3, 89.2]

4.3.2 Procedure

4.3.2.1 Laboratory experiment

All participants performed the Meyer and Flenghi (1995) step-test, which has the following advantages: simple, cost-effective, and practical, it can be implemented safely without imposing high cardiac strain, particularly for older and less active individuals. Imbeau et al. (2010) demonstrated that the highest exertion level on this test reached by a group of forest workers corresponded well to the exertion generally measured during typical regeneration release work.

This step-test has been validated against other graded submaximal exertion tests (Meyer and Flenghi, 1995) and against a maximal treadmill test (Imbeau et al., 2009). An additional advantage is that step frequency (15 steps per min paced with a metronome) is sufficiently low for any worker to be able to keep pace at all four step heights, for superior overall test precision and robustness. The equipment consists of a lightweight portable bench with a height-adjustable step (11.5, 21.5, 31.5, and 41.5 cm). After a 5-minute sitting rest to obtain the resting heart rate (HR_{rest}), participants were asked to stand in front of the bench for 2 minutes. The test started with the participant stepping onto and off the lowest step height for 3 minutes, followed by a short, 30-second standing rest in front of the bench while the experimenter increased the step height by sliding the step out of the lowest set of tracks and into the second-height tracks. This 3.5-minute cycle was then repeated for the three remaining step heights. The participant's heart rate and oxygen consumption were continuously measured during the test using a heart rate monitor (Polar Electro T-61 coded) and a portable oximeter (Cosmed Fitmate PRO), respectively. The laboratory study dataset included the VO_2-HR measurements collected at rest and for each step height of the step-test.

4.3.2.2 Field experiment

Regeneration release work involves variable workload intensities as a result of varied work conditions (e.g., sloping terrain, field obstacles, vegetation density, and stem diameters to be cut) (Toupin et al., 2007). The 8 forest workers who participated in the field experiment performed the Meyer and Flenghi step-test in the morning shortly after their arrival to the worksite, on the edge of the road close to the patch that had to be cleared during the day. According to Meyer and Flenghi (1995), one advantage of their test is that it was developed such that it can be administrated at the beginning of a workday without compromising a participants' ability to perform physical work throughout his work shift because of undue fatigue. During the test, heart rate and oxygen consumption were continuously measured with the same portable devices as in the laboratory experiment. Participant's HR_{rest} was determined during the 5-min rest preceding the test. Upon completion of the step-test, the worker was released and started his regular workday. Worker heart rate was continuously measured throughout the day using the Polar Electro while oxygen consumption was measured with the Cosmed Fitmate PRO for an average duration of 37 min (range: 34 to 53 min) around mid morning. The Cosmed Fitmate PRO could not be used any longer since it was deemed uncomfortable by the workers. Nonetheless, the field VO_2 measurements provided a means to validate the energy expenditure estimates produced by the different models with heart rate data as their main input. The field study dataset included the VO_2-HR measurements collected during the early morning step-test as well as VO_2-HR measurements collected during work for all 8 workers. As with any existing HR-based VO_2 estimation method, the HR data collected during work were corrected by one of the authors using the method proposed by Vogt et al. (1970, 1973) to remove the thermal component (or thermal pulse) from the field-measured HR data. This HR increase is related to an increase in body core temperature owing to work in hot conditions (Rowell, 1986; Kampmann et al., 2001) and it may lead to a significant VO_2 overestimation when a participant's VO_2-HR relationship from the morning step-test is used to estimate his work VO_2 from HR measurements in the field.

4.3.3 Models development

A two-step approach was followed for models development (Figure 4-1). First, four "individualized" models for estimating VO_2 from HR data were developed using each participant's step-test data from the laboratory experiment (N=27 participants with 42 data samples per participant). Two of the models were developed using ANFIS and analytical methods, respectively. The other two models used traditional linear calibration and Flex-HR methods, respectively. Models quality of fit were compared. Next, a General ANFIS model was trained using the step-test data from a random sample of 19 laboratory participants. The HR data from the remaining 8 laboratory participants were fed to the General ANFIS model to generate VO_2 estimates that were compared with corresponding VO_2 measurements.

In the second step (field study) data from the early morning step-test (N=8 participants with 42 data samples per participant) were used to develop four "individualized" models for each one of the 8 forest workers. Next, regeneration release work HR data (148 data samples per participant on average) were fed to the individualized models as well as to the General ANFIS model developed previously from laboratory data to produce work VO_2 estimates that were compared with work VO_2 measurements.

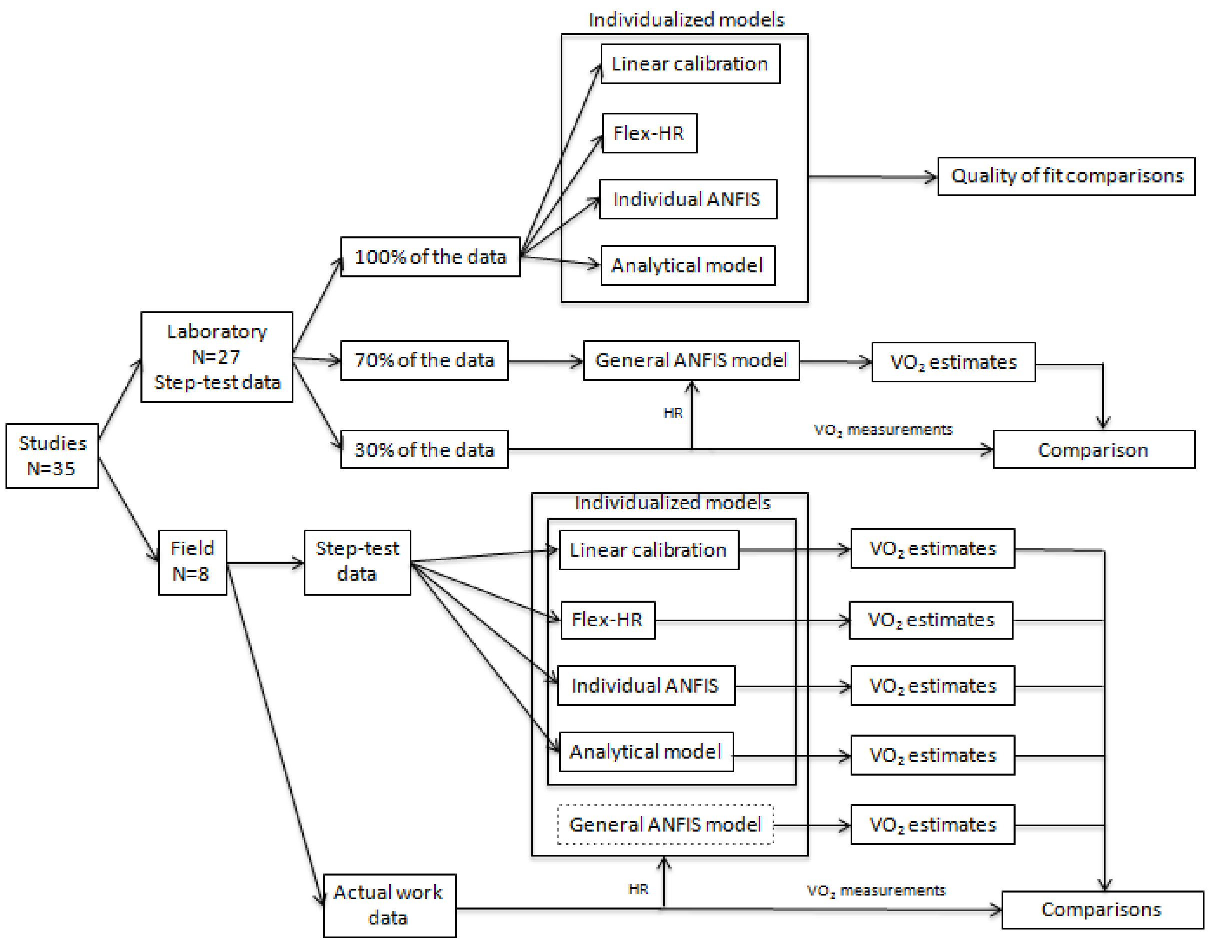

Figure 4-1: Schematic description of the study

4.3.3.1 ANFIS model

The individualized ANFIS model developed with each participant's data was associated with clustering parameters that were specific to the participant and hence used a specific rule-base. For example, the clustering parameters selected for Participant 3 were: $r = 0.5$, $\eta = 1.25$, $\bar{\epsilon} = 0.5$ and $\underline{\epsilon} = 0.15$. As a result, three fuzzy rules were associated with the Participant 3's ANFIS model (Appendix A). The individual ANFIS was then trained for 100 epochs using 41 samples from Participant 3's data. The developed ANFIS model for this participant estimates VO_2 with a 1.0 (ml/kg.min) *RMSE* and $R^2 = 0.97$ (Figure 4-2).

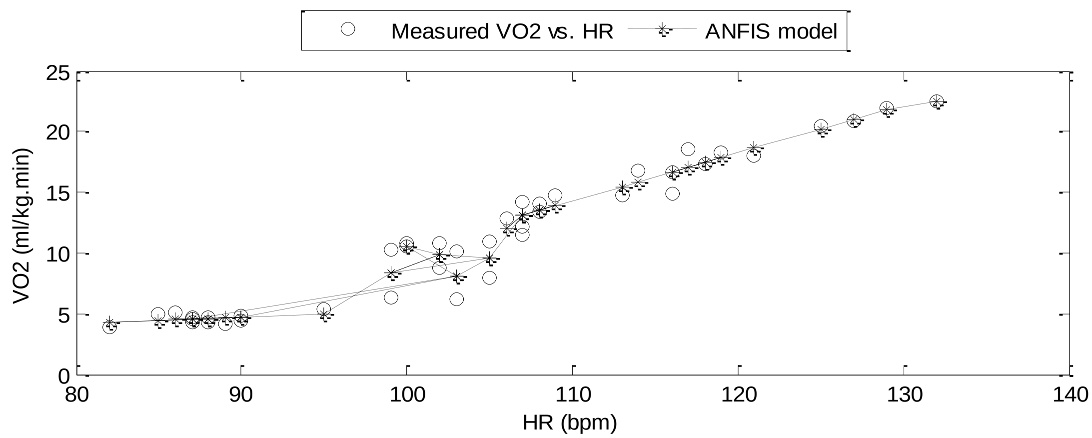

Figure 4-2: Participant 3 ANFIS model for estimating VO_2 as a function of HR

4.3.3.2 Analytical model

A careful analysis of the laboratory data collected for each participant pointed to a bilinear relationship between HR and VO_2, that is a relationship known as a "bilinear frontier" defined as a boundary formed by two half lines intersecting at one point (Labib and Khattar, 2010). A previous study by Schulz et al. (1989) supported this idea as they represented the curve describing the relationship between HR and VO_2 using two straight lines.

A unit step function is used to indicate the absence of the linear behaviour at low workload intensities. As shown in Figure 4-3, the curve describing the relationship between HR and VO_2 over the range of all workload intensities can be represented as follows:

$$f(x) = (ax - b).u\left(x - \frac{b}{a}\right) + c \qquad (4.1)$$

where $a, b, c > 0$. x and $f(x)$ indicate *HR* and VO_2, respectively. The transition point in the heart rate profile that separates between low and moderate workload intensities is denoted by b/a while

c represents a shift along the y-axis indicating the initial VO_2 value during low workload intensity. For simplicity, the unit step function was approximated using the logistic function:

$$f(x) \cong (ax-b).\left[\frac{1}{1+e^{-p\left(x-\frac{b}{a}\right)}}\right]+c \qquad (4.2)$$

or

$$VO_2 \cong (a.HR-b).\left[\frac{1}{1+e^{-p\left(HR-\frac{b}{a}\right)}}\right]+c \qquad (4.3)$$

where p denotes a smoothing parameter such that a larger p corresponds to a sharper transition at x or $HR = b/a$.

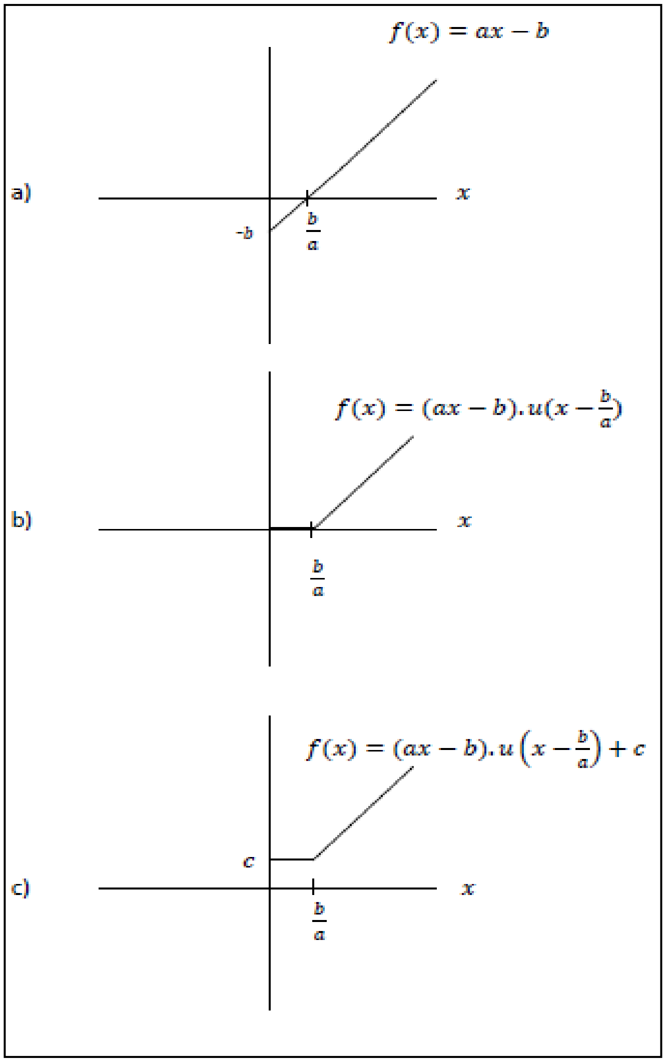

Figure 4-3: Analytical model based on the Heaviside function: (a) straight line starting at $x = 0$ (b) straight line starting at $x = b/a$ (c) straight line starting at $x = b/a$ and shifted c units in the y-axis

A Heaviside-based analytical model was developed for each one of the 27 participants by optimizing the parameters *a, b, c* and *p* such that the bilinear curves represented by equation (3) would best fit the each participant's data. The Trust-Region Reflective Newton algorithm was used to solve the nonlinear optimization problem using MATLAB 7.5.0. This algorithm represents an improvement over the popular Levenberg-Marquardt algorithm and it is considered as one of the most efficient algorithms in solving difficult nonlinear optimization problems (Coleman and Li, 1996). For example, analysing the VO_2-HR data collected from Participant 3 yielded the following Heaviside-based analytical model (Figure 4-4):

$$VO_2 \cong (0.4452 \times HR - 40.19) \times \left[\frac{1}{1+e^{-0.2304(HR-90.274)}}\right] + 4.917 \qquad (4.4)$$

with *RMSE* = 1.3 (ml/kg.min) and R^2 = 0.95.

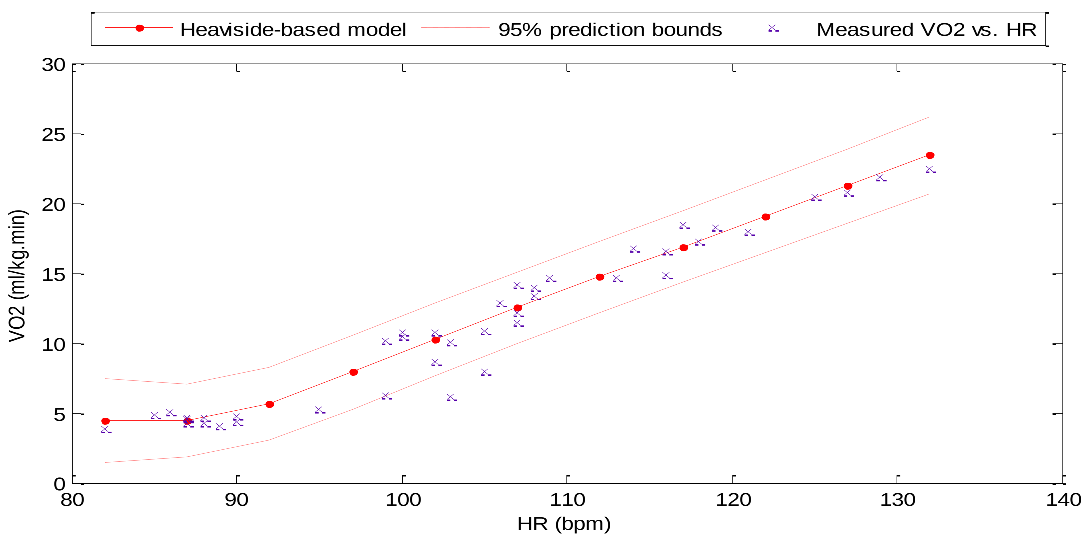

Figure 4-4: Participant 3 analytical model for estimating VO_2 as a function of HR

4.3.3.3 Traditional linear calibration and Flex-HR models

The traditional linear calibration model is a VO_2-HR linear regression equation created for each participant using his laboratory step-test data (Schulz et al., 1989; Bouchard and Trudeau, 2008). For instance, the linear regression equation created from Participant 3's data was:

$$VO_2 = 0.4393 \times HR + 34.4118 \qquad (4.5)$$

with *RMSE* = 1.5 (ml/kg.min) and R^2 = 0.94.

The Flex-HR model uses four parameters (resting VO_2, Flex-HR point, slope and intercept of the linear portion of the VO_2-HR relationship) to establish a participant's calibration curve (Spurr et al., 1988; Ceesay et al., 1989). The Flex-HR point was determined as the average of the lowest HR during the step-test and the highest HR during the sitting rest preceding the test (Valanou et al., 2006). Above the Flex-HR point, a linear regression equation was created from the corresponding VO_2-HR data, while the average of VO_2 values measured during sitting at rest was determined as the resting VO_2. For instance, the parameters associated with Participant 3 were as follows: resting VO_2 = 5.8 ml/kg.min, Flex-HR point = 101 bpm, slope = 0.41 and intercept = -31.3. These parameters describing the Flex-HR model for Participant 3 yielded a *RMSE* = 1.4 (ml/kg.min) and $R^2 = 0.94$.

4.3.3.4 General ANFIS model

The ANFIS model was developed using VO_2 and HR laboratory step-test data. Measured HR and HR_{rest} were used as input variables to the General ANFIS model while VO_2 was used as the output variable. Several studies have recommended the 70% / 30% randomly selected proportions of data for model training/validation (Kutner et al., 2004; Abu Bakar and Tahir, 2009). Therefore, the data from 19 randomly selected participants (798 data samples) were used to train the model (each participant providing 42 samples), while the data from the remaining 8 participants (336 data samples) were used to produce model estimates. An enumerative search for optimal determination of subtractive clustering parameters yielded the following selection of parameters: $r = 0.9$, $\eta = 1.5$, $\bar{\epsilon} = 0.9$ and $\underline{\epsilon} = 0.9$. As a result, three clusters were identified each corresponding to one fuzzy IF-THEN rule. Once the initial FIS was developed, it was put in a neural network framework to optimize the rules parameters (premise and consequent parameters).

The back-propagation gradient descent method in combination with the least squares method for 20 epochs were used to train the model (MATLAB version 7.5.0 with fuzzy logic toolbox, see Appendix B). It contains three fuzzy IF-THEN rules, with three Gaussian membership functions assigned to each input variable, and the total number of modifiable parameters is 21 (12 premise and 9 consequent parameters), see Appendix C. Since the number of training samples was several times larger than the number of modifiable parameters being estimated and given that the training and the testing data sets were obtained from different participants, the General ANFIS model was expected to achieve good generalization capability (Yildiz et al., 2009).

4.3.4 Models comparisons

The quality of fit of the individualized models were compared for HR values throughout the HR range as well as for three HR categories: very light work: <80 bpm; light work: 80-100 bpm; and moderate to heavy work: >100bpm (Smolander et al., 2008). The VO_2 estimates from the General ANFIS model using the data from the remaining 8 laboratory participants that had not been used to develop that model were compared with VO_2 measurements across the complete HR range as well as for the three HR categories. The HR data measured during actual work in the field were used to generate work VO_2 estimates with the five models (four individualized models developed from field step-test data and the General ANFIS model developed with laboratory data) that were compared with the VO_2 measurements made during actual regeneration release work.

4.3.5 Statistical analysis

The quality of fit of the models and the comparisons among models were evaluated using: the root mean square error (RMSE) and the mean absolute percentage error (MAPE) between the measured and the model estimated VO_2 (Azadeh et al., 2010). Student's two-tailed t-test for paired observations was used to test for differences between the values to be compared. A threshold of $p < 0.05$ was considered for statistical significance. Limits of agreement (LOA) between the measured VO_2 values and the values estimated by the General ANFIS model and traditional estimation models (linear calibration and Flex-HR) were determined using the Bland-Altman plot to examine the accuracy of the estimation models (Bland and Altman, 1986). Moreover, the coefficient of variation (CV= standard deviation/sample mean*100) was used to evaluate the performance of all VO_2 estimation models.

4.4 Results

Table 4.2 summarises the results obtained for each model and for each study's data. It reports the mean of all participants' average VO_2 estimation per model as well as the corresponding mean RMSE and MAPE for the whole HR range and separately for the three HR categories. In addition, it includes a ranking of the different VO_2 estimation model performance using the data from the two studies.

Table 4.2: Summary of results from laboratory and field studies

Type	HR range (bpm)	Measured VO_2 (ml/kg.min)	Linear calibration			Flex-HR method			Individual analytical			Individual ANFIS			General ANFIS		
			$\widehat{VO}_2$	RMSE	MAPE/ MAE	$\widehat{VO}_2$	RMSE	MAPE/ MAE	$\widehat{VO}_2$	RMSE	MAPE/ MAE	$\widehat{VO}_2$	RMSE	MAPE/ MAE	$\widehat{VO}_2$	RMSE	MAPE /MAE
Laboratory data	**Overall HR range (n=27)**	11.3	11.5 +2.1% **	1.7 (4)	17.0/ 1.9 (4)	11.3 -0.04%	1.3 (2)	11.3/ 1.3 (2)	11.3 +0.05%	1.5 (3)	13.5/ 1.5 (3)	11.3 -0.01%	1.0 (1)	8.2/ 0.9 (1)	NA	NA	NA
	Overall HR range (n=8)	10.9	10.2 -6.8% [20.4] *	1.5 (4)	16.1/ 1.8 (4)	10.0 -8.1% [15]	1.3 (2)	12.4/ 1.4 (2)	10.0 -8.1%	1.4 (3)	13.9/ 1.5 (3)	10.0 -8%	0.9 (1)	7.9/ 0.9 (1)	11.3 +3.4% [18.8]	2.0 (5)	19.2/ 2.1 (5)
	Lower range HR<80	4.6	4.9 +7.5% [20.9]	0.5 (4)	8.5/ 0.4 (4)	4.8 +5.5% [3.5]	0.3 (2)	5.5/ 0.3 (2)	5.0 +8.7% *	0.5 (3)	8.5/ 0.4 (3)	4.6 +1.5%	0.1 (1)	1.4/ 0.1 (1)	5.1 +11.9% [17.2] *	1.2 (5)	23.6/ 1.1 (5)
	Medium range 80≤HR≤100	11.2	11.2 -0.3% [21.4]	0.3 (3)	2.2/ 0.3 (3)	11.2 -0.3% [20.5]	0.2 (2)	1.2/ 0.1 (2)	10.8 -3.6% *	0.5 (4)	3.6/ 0.4 (4)	11.2 -0.5%	0.1 (1)	0.5/ 0.1 (1)	11.7 +4.6% [20.8]	1.5 (5)	15.4/ 1.7 (5)
	Higher range HR>100	14.3	14.6 +1.9% [19.1] *	0.4 (4)	1.9/ 0.3 (4)	14.4 +0.3% [18.1]	0.2 (2)	0.9/ 0.1 (2)	14.4 +0.3%	0.3 (3)	1.0/ 0.1 (3)	14.3 -0.01%	0.1 (1)	0.2/ 0.0 (1)	15.0 +4.9% [18]	1.7 (5)	9.0/ 1.3 (5)
Field data	**Overall HR range (n=8)**	19.9	19.1 -3.8% [24.1]	3.6 (5)	21.7/ 4.3 (4)	18.9 -4.7% [19.4] **	3.6 (4)	19.6/ 3.9 (3)	19.9 +0.01%	3.2 (2)	17.5/ 3.5 (2)	19.9 -0.01%	2.8 (1)	14.1/ 2.8 (1)	19.8 -0.3% [15.5]	3.5 (3)	22.3/ 4.4 (5)
	Lower Range HR<80	7.0	5.9 -15.8% [36.2]	2.1 (5)	21.5/ 1.5 (5)	6.4 -8% [16.7]	1.0 (3)	11.8/ 0.8 (3)	6.9 -0.14%	0.5 (2)	5.9/ 0.4 (2)	7.0 +0.9%	0.1 (1)	1.5/ 0.1 (1)	7.3 +5.0% [21.8]	1.7 (4)	18.0/ 1.3 (4)
	Medium range 80≤HR≤100	12.8	13.9 +9.2% [28.2]	3.0 (4)	23.7/ 3 (4)	13.6 +6.5% [35.3]	2.9 (3)	19.4/ 2.5 (3)	14.0 +9.7%	2.0 (2)	14.1/ 1.8 (2)	13.1 +2.6%	0.6 (1)	3.4/ 0.4 (1)	13.1 +2.7% [18.6]	3.2 (5)	26.1/ 3.3 (5)
	Higher range HR>100	28.4	27.2 -4.3% [10.3]	1.5 (3)	4.3/ 1.2 (3)	27.0 -4.9% [9.8]	1.8 (4)	5.6/ 1.6 (4)	28.2 -0.7%	0.3 (2)	0.8/ 0.2 (2)	28.3 -0.2%	0.1 (1)	0.2/ 0.1 (1)	27.0 -4.8% [7.9]	2.8 (5)	8.6/ 2.5 (5)

Note. $\widehat{VO}_2$: estimated oxygen consumption (ml/kg.min); RMSE: root mean square error (ml/kg.min); MAPE: mean absolute percentage error (%); MAE: mean absolute error (ml/kg.min); *p < 0.05, **p < 0.001 significantly different from the measured VO_2; ( ): model performance ranking w.r.t. estimation errors; %: percentage difference w.r.t. measured VO_2; [ ]: coefficient of variation (%).

4.4.1 Laboratory data analysis

Results show that among the four individualized models developed with all 27 laboratory participants' data, the analytical and the linear calibration models overestimated measured VO_2 with overall mean differences of 0.01 and 0.2 ml/kg.min, respectively, whereas the individual ANFIS and the Flex-HR models underestimated measured VO_2 with overall mean differences of 0.001 and 0.004 ml/kg.min, respectively. When using only the data from the 8 laboratory participants not used to train the General ANFIS model, results showed much larger absolute differences between mean predicted and mean measured VO_2 for all four individualized models: 0.7 ml/kg.min for the linear calibration model, 0.9 ml/kg.min for the Flex-HR and the analytical models and 0.9 ml/kg.min for the individualized ANFIS. The General ANFIS model, on the other hand, overestimated the measured VO_2 values with a 50% smaller overall mean difference (0.4 ml/kg.min).

The VO_2 relative difference associated with the interval HR<80 bpm was smallest with the individual ANFIS model (1.5%) and largest with the General ANFIS model (11.9%). In the interval 80<HR<100 bpm, the smallest relative difference was obtained with the linear and Flex-HR models (0.3%), whereas the highest relative difference was obtained with the General ANFIS model (4.6%). The relative difference associated with the interval HR>100 bpm was smallest with the individual ANFIS model (0.01%) and highest with the General ANFIS model (4.9%).

In terms of model estimation errors, results based on both the 27 and the 8 participants indicated the outperformance of the developed individual ANFIS over the other three individual models. Similarly, for different HR categories, the individual ANFIS model yielded the smallest relative estimation errors whereas the General ANFIS model yielded the highest relative errors. Paired t-tests showed that the linear calibration model produced statistically significant differences between estimated and measured VO_2 that could be observed throughout the HR range either with 27 or 8 participants, as well as in the higher HR range (Table 4.2). The analytical model overestimated significantly in the lower HR range and underestimated in the medium HR range. The General ANFIS model overestimated significantly in the lower HR range.

The Bland-Altman plot in Figure 4-5(a) depicts the limits of agreement (LOA) between the measured and estimated (i.e., by General ANFIS, linear calibration and Flex-HR models) VO_2 values. The differences between the General ANFIS and VO_2 measurements tend to decrease at low intensity levels compared with the linear calibration and Flex-HR models, whereas the opposite can be observed at higher intensity levels. The standard deviation figures and the LOA presented in Table 4.3 confirm this observation; compared with the other models in the lower HR range, the LOA are narrower for the General ANFIS and they increase with intensity level.

4.4.2 Field data analysis

Results from the field study show that the linear calibration and Flex-HR models yielded larger mean prediction differences than in the laboratory (0.8 and 0.9 ml/kg.min, respectively) whereas the individual ANFIS and the analytical models yielded much smaller errors (0.001 and 0.002 ml/kg.min) across the overall HR range. The General ANFIS model underestimated the mean measured VO_2 by 0.1 ml/kg.min (Table 4.2). In the lower HR range, the relative difference between the measured VO_2 values and the estimated values was smallest (0.01 ml/kg.min) with the analytical model and highest (1.1 ml/kg.min) with the linear calibration model. In the medium HR range, the relative difference was smallest (0.3 ml/kg.min) for the individual ANFIS model and highest (1.2 ml/kg.min) for the analytical model. In the higher HR range, the smallest relative difference was produced by the individual ANFIS (0.1 ml/kg.min), while the highest was with the Flex-HR model (1.4 ml/kg.min).

Rankings based on estimation errors show that the individual ANFIS model outperformed the other models (Table 4.2) while the analytical model provided second best performance. The General ANFIS performed comparably or slightly better on the overall HR range and for the lower HR range when compared to the linear calibration and Flex-HR models but, it produced the largest estimation errors in the medium and higher HR ranges.

The paired t-test showed no significant difference between the mean measured VO_2 and the mean VO_2 estimated by any of the models, except for the Flex-HR model on the overall HR range. The Bland-Altman plot in Figure 4-5(b) shows the General ANFIS's prediction with field data generally comparable to that of the other models. Bias and SD figures in Table 4.3 indicate that the General ANFIS performs better than the other two models in the lower HR range. It performs comparably in the higher HR range and worse in the mid-range.

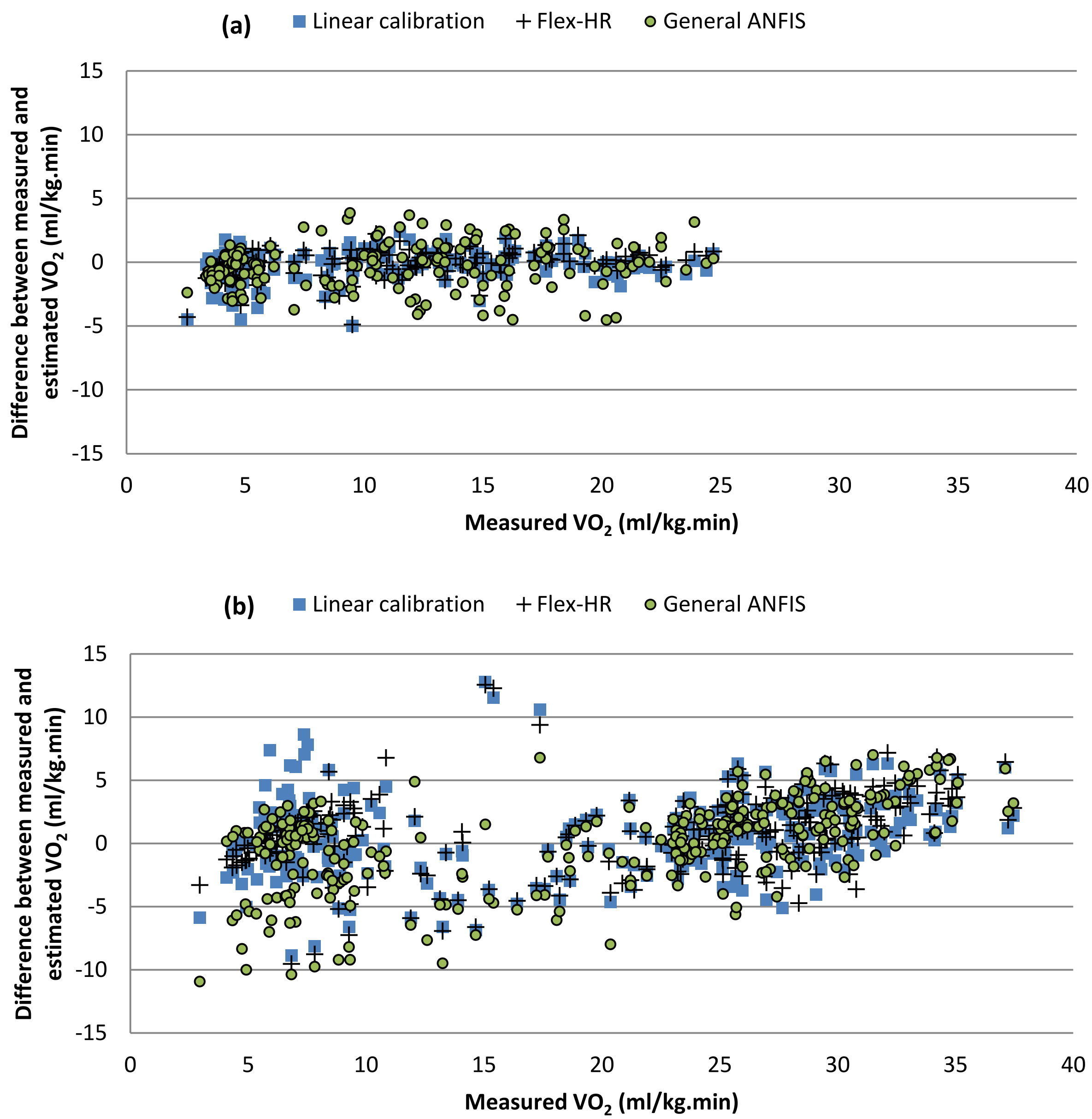

Figure 4-5: Bland-Altman plots to test the agreement between measured and estimated VO_2 values with: (a) laboratory data (b) field data

Table 4.3: Bias and LOA associated with VO_2 estimation models with respect to measured VO_2 in laboratory and field

Type	HR range (bpm)	Models	Bias (ml/kg.min)	SD (ml/kg.min)	Limits of agreement (LOA)	
					Lower limit (ml/kg.min)	Upper limit (ml/kg.min)
Laboratory data	Overall HR range (n=8)	Linear calibration	-0.2	1.2	-2.6	2.3
		Flex-HR	-0.2	1.0	-2.1	1.9
		General ANFIS	-0.3	1.8	-3.9	3.2
	Lower range HR<80	Linear calibration	-0.2	1.2	-2.6	2.6
		Flex-HR	-0.3	0.8	-1.9	1.4
		General ANFIS	-0.7	0.9	-2.5	1.2
	Medium range 80≤HR≤100	Linear calibration	-0.1	1.4	-3.0	2.7
		Flex-HR	-0.2	1.2	-2.4	2.1
		General ANFIS	-0.02	1.9	-3.7	3.7
	Higher range HR>100	Linear calibration	-0.2	0.9	-2.0	1.7
		Flex-HR	0.1	0.8	-1.5	1.7
		General ANFIS	-0.4	2.0	-4.4	3.6
Field data	Overall HR range (n=8)	Linear calibration	0.8	3.1	-5.3	6.9
		Flex-HR	0.9	2.9	-4.7	6.5
		General ANFIS	0.1	3.5	-6.8	6.9
	Lower Range HR<80	Linear calibration	1.5	3.0	-4.3	7.3
		Flex-HR	0.9	2.0	-3.1	4.9
		General ANFIS	-0.2	2.5	-5.1	4.7
	Medium range 80≤HR≤100	Linear calibration	0.3	4.1	-7.8	8.4
		Flex-HR	0.7	3.9	-7.0	8.3
		General ANFIS	-1.9	4.3	-10.4	6.5
	Higher range HR>100	Linear calibration	0.9	2.6	-4.2	6.0
		Flex-HR	1.3	2.6	-3.9	6.4
		General ANFIS	1.0	2.9	-4.7	6.7

Note. HR: heart rate (bpm); Bias: average difference between measured and estimated VO_2 values (ml/kg.min); SD: standard deviation of the difference between measured and estimated VO_2 values (ml/kg.min); LOA: limits of agreement between the measured and the estimated VO_2 values (ml/kg.min).

4.5 Discussion

A key objective of this study was to develop an approach that is simpler and more practical than the current methods that require collecting individual calibration data on a number of workers when it comes to estimating work activity VO_2 values from HR measurements. The

General ANFIS model proposed here takes advantage of recent mathematical methods/software to improve on methods currently used by practitioners and many researchers to fit this purpose. As expected from the outset, the General ANFIS model was not the most accurate of the models compared in this paper since it does not use individual calibration data once it is developed. Laboratory results showed that the General ANFIS tended on average to slightly overestimate the measured VO_2 values during very light (0.5 ml/kg.min), light (0.5 ml/kg.min) and moderate-to-heavy (0.7 ml/kg.min) work (Table 4.2). The difference was statistically significant for the lower HR range (+11.9%), however it is comparable to the ±10% figure generally expected when estimating the metabolic rate based on HR measurements using the linear calibration method (ISO 8996, 2004).

On the other hand, the General ANFIS model performed better with field data with average estimation errors under 5%, that is an error magnitude generally expected with direct VO_2 measurement methods (ISO 8996, 2004). Prediction performance of the General ANFIS model using field data was generally better on average than that of the linear calibration and Flex-HR models according to the metrics described in Table 4.2, and comparable as indicated by LOA analysis (Table 4.3). The results also show that the General ANFIS model provides better prediction in the lower HR range than the linear calibration method, thus indicating a better ability in dealing with the nonlinearity between VO_2 and HR at low intensity levels. This study shows the General ANFIS model to be a practical, low cost and very efficient replacement for the linear calibration and Flex-HR since it can be used directly to predict VO_2 values from HR measured during work. Although adequate knowledge of MATLAB was required to develop the model, it has been implemented in Excel (Appendix E) so that researchers and practitioners can apply it easily as a decision support tool. (A complete Excel file implementing the model can be obtained by contacting the first author of the paper). Appendix D provides a General ANFIS model that was trained with all laboratory data. This general model is expected to perform better than the general model that was trained with only 19 participants since it yielded a slightly higher R-square fitting parameter (0.94 vs. 0.92).

A secondary objective in this study was to tackle the problem of uncertainty and nonlinearity that exist in traditional VO_2 estimation methods, especially at low workload intensity. Therefore, new approaches were proposed, namely the individual ANFIS and the analytical models. Results from laboratory and field studies showed the outstanding superiority of the proposed individualized ANFIS over the more traditional models (linear calibration and Flex-HR) throughout the whole HR range observed, and separately for different HR ranges. Table 4.4 shows the percentage reductions in RMSE and MAPE that can be achieved when preferring the individual ANFIS over the individualized traditional models tested in this paper. Hence, where individual calibration data is available and best prediction must be achieved, the individual ANFIS model should be preferred. As our results show, better precision can only be achieved at the expense of increased cost of implementation of the method (i.e., individual participant calibration data collection).

Table 4.4: Percentage reduction (%) in estimation errors when using proposed individual models instead of the traditional models

Proposed models	**Type of studies**	**Traditional models**			
		Linear calibration		**Flex-HR model**	
		RMSE	MAPE	RMSE	MAPE
Individual ANFIS	Laboratory	39.3	51	30.1	36.3
	Field	22.6	34.8	22.2	34.8
Analytical model	Laboratory	8.5	13.8	-5.3	-12
	Field	12.2	19.1	11.7	10.3

Note. RMSE: root mean square error (ml/kg.min); MAPE: mean absolute percentage error (%); (-) sign: increase in estimation error.

The model performance statistics from this study are coherent with the recent literature. For instance, the traditional linear calibration method has been reported to yield mean absolute errors (MAE) during the overall HR range of approximately 3.7 ml/kg.min (Firstbeat Technologies, 2007) and 4 ml/kg.min (Pulkkinen et al., 2004; Smolander et al., 2008). These results fairly agree with our findings over the full HR range (1.9 and 4.3 ml/kg.min with laboratory and field data, respectively). The smallest, median and largest MAE values obtained in different HR ranges with laboratory and field data were 0.3, 1.5 and 4.3 ml/kg.min, respectively (Table 4.2). Other studies found that this method yielded MAPE figures over the full HR range of 16.8% (Schulz et al., 1989) and 15%-25% (Firstbeat Technologies, 2007), which are coherent with our findings (17% and 21.7% for the laboratory and field data, respectively). The smallest, median and largest MAPE obtained in different HR ranges with laboratory and field data were 1.9%, 16.1% and 23.7%, respectively. For the Flex-HR method, Firstbeat Technologies (2007) reported a 13.5% MAPE, while Ceesay et al. (1989) reported a RMSE of 1.3 ml/kg.min. These figures compare to our laboratory results (MAPEs ranging from 0.9 to 12.4 %, and RMSEs ranging from 0.2 to 1.3 ml/kg.min). Firstbeat Technologies (2005) proposed a general neural network-based method for VO_2 estimation based on both HR and heart rate variability, which gives additional information on respiration rate and/or on-off response phases. During simulated real-life tasks in a laboratory study, Pulkkinen et al. (2004) found this method to yield a MAE of approximately 2.5 ml/kg.min. In comparison the General ANFIS model proposed here yielded better performance with laboratory data (MAE = 2.1 ml/kg.min, range = 1.1 to 2.1 ml/kg.min) and a slightly reduced performance with field data (MAE = 4.4 ml/kg.min, range = 1.3 to 4.4 ml/kg.min). The linear calibration model has been reported to yield a coefficient of variation (CV) of 19.1% (Bouchard and Trudeau, 2008), 21% (Schulz et al., 1989) and 29.6% (Anjos et al., 2007) over the full HR range. Also, it has been reported that the Flex-HR model yields a CV of 16.7% (Ceesay et al., 1989) and 18.6% (Spurr et al., 1988) over the full HR range. Our findings show comparable relative variations with laboratory data (20.4% and 15% for the linear calibration and Flex-HR, respectively) and field data (24.1% and 19.4% for the linear calibration and Flex-HR, respectively) (Table 4.2). In addition, the General ANFIS model proposed here yielded CVs of 18.8% (range = 17.2% to 20.8%) with laboratory and 15.5% (range = 7.9% to 21.8%) with field data, respectively, indicating a relative precision comparable to or better than that of the traditional individual estimation methods (Table 4.2).

Practitioners should be aware that the models developed in this study will overestimate VO_2 when a significant thermal pulse is present. Hence, the HR thermal component must be removed at the data preparation stage prior to use (Vogt et al., 1970, 1973). Thanks to recent technological developments, core temperature can now be measured easily and noninvasively during actual work (e.g., VitalSense), and could be included as an input variable in the General ANFIS model. To improve robustness and generalizability of the models, further studies could include a larger number and variety of participants and a variety of actual work activities for General ANFIS training and validation. Investigating the influence of different membership functions (i.e., triangular) and incorporating other easily measured variables (e.g., age, weight, body mass index and physical fitness) could further improve model performance.

4.6 Conclusion

This paper presented new approaches for VO_2 estimation based on HR measurements. In the first part of the paper, individual ANFIS and analytical models were proposed for VO_2

estimation so as to treat the nonlinearity and uncertainty associated with physiological variables. Results indicated the better performance of the individual ANFIS (based on laboratory and field data) and analytical (based on field data) models over the traditional VO_2 estimation models (linear calibration and Flex-HR). Therefore, the proposed individualized models and preferably the individual ANFIS, should be used in small population work environments or when very accurate VO_2 estimation is desired. This paper also presented a General ANFIS model for VO_2 estimation that does not require individual calibration data to be obtained. Results indicated the similarity between the measured VO_2 and estimates from the General ANFIS model. This strongly implies that the General ANFIS model can replace the traditional VO_2 estimation models especially in large population work environments where one cannot afford to have each participant take a graded exercise test and yet obtain a VO_2 estimation that provides reasonable (±10%) accuracy. The proposed models do not only represent a new application of fuzzy logic for VO_2 estimation, but they also can be implemented as easily as the traditional models due to the rapid software advancements in recent years.

4.7 Acknowledgements

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CHAPTER 5: ARTICLE 2 – ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS WITH K-FOLD CROSS-VALIDATION FOR ENERGY EXPENDITURE PREDICTIONS BASED ON HEART RATE

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5.1 Abstract

In a new approach based on adaptive neuro-fuzzy inference systems (ANFIS), easily determined variables were used to estimate oxygen consumption (VO_2). The ANFIS prediction model consists of three ANFIS modules for estimating the Flex-HR parameters. Fifty-eight participants performed the Meyer and Flenghi step-test, during which heart rate and oxygen consumption were measured. Results indicated no significant difference between observed and estimated Flex-HR parameters and between measured and estimated VO_2 in the overall HR range, and separately in different HR ranges. The ANFIS prediction model (MAE = 3 ml/kg.min) demonstrated better performance than Rennie et al.'s (MAE = 7 ml/kg.min) and Keytel et al.'s (MAE = 6 ml/kg.min) models, and comparable performance with the standard Flex-HR method (MAE = 2.3 ml/kg.min) throughout the HR range. The ANFIS model thus provides practitioners with a practical, cost- and time-efficient method for VO_2 estimation without the need for individual calibration.

Keywords: Flex-HR method; physical workload; adaptive neuro-fuzzy inference system (ANFIS)

5.2 Introduction

Researchers in occupational health and safety have demonstrated the importance of designing jobs according to the physiological capacity of a particular workforce. Studies have shown that such design, based on the balance between physiological capacity of workforce and energetic demands of physical jobs, is a key factor in maintaining workforce safety and productivity (Abdelhamid, 1999; Wu and Wang, 2002; Dempsey et al., 2008). Oxygen consumption (VO_2) reflects energy expenditure (EE) and physical workload associated with physically demanding jobs (Smolander et al., 2008; Wu and Wang, 2002; Bouchard and Trudeau, 2008).

Direct measurement of VO_2 requires sophisticated and costly devices; therefore attempts have been made to find alternative estimation methods (e.g., ISO-8996, 2004; Smolander et al., 2008). The Flex-HR method is one of the most widely used methods based on heart rate (HR) measurements (Spurr et al., 1988; Ceesay et al., 1989; Schultz et al., 1989; Garet et al., 2005). It assumes a linear relationship between HR and VO_2 above a transition point (Flex point) and a more variable relationship, which uses the average of HR values during rest, below this point (Garet et al., 2005; Valanou et al., 2006). The Flex point is empirically defined as the average of the lowest HR during exercise and the highest HR during rest (Valanou et al., 2006). Accordingly, the Flex-HR method is based on four parameters, namely resting oxygen consumption (VO_2rest), the Flex point, the slope, and the intercept of the linear function describing the VO_2-HR relationship above the Flex point. The main criticism of the Flex-HR method is the impracticality of establishing individual calibration curves at workplaces with large populations, since it takes at least 45 minutes per participant (Rennie et al., 2001). Another criticism concerns the uncertainty in determining the Flex point due to several factors, such as the physical and physiological characteristics of the population under study, as well as the type and number of physical activities (Garet et al., 2005). Group calibration methods have been used to estimate energy expenditure from HR (Li et al., 1993; Luke et al., 1997; Rutgers et al., 1997; Rennie et al., 2001; Keytel et al., 2005). These methods were based on linear prediction models using regression and mixed-model analyses, which require a large sample size and lack the ability to capture nonlinearity, uncertainty and the true relationship between variables in the human physiological system (Shimizu and Jindo, 1995; Park and Han, 2004). In recent years, artificial intelligence (AI) techniques have been proposed as alternatives to conventional statistical methods (Jang et al., 1997; Kaya et al., 2003; Yildirim and Bayramoglu, 2006). One of the most effective AI techniques, particularly for nonlinear function approximation, is the adaptive neuro-fuzzy inference system (ANFIS). It combines the unique ability of fuzzy logic to make decisions in uncertain conditions with the learning and adaptive capabilities of artificial neural networks. ANFIS has consistently been demonstrated effective in approximating nonlinear functions, particularly in biomedical engineering (Güler and Übeyli, 2004, 2005; Übeyli and Güler, 2005a, 2005b).

This study presents a new approach to estimating VO_2 using HR without the need for an individual calibration test. The proposed approach attempts to improve the standard Flex-HR method so as to be suitable for large-scale workplaces. Three ANFIS modules forming the ANFIS prediction model were developed for the estimation of the Flex-HR parameters from measurements that can be easily obtained in field. Once the Flex-HR parameters are estimated, individuals' VO_2 during different activities can be determined. Laboratory and field data collection were conducted for the ANFIS prediction model development and testing. The ANFIS prediction model was compared with measured VO_2 values and three VO_2 estimation methods, namely the standard Flex-HR method, Rennie et al.'s (2001), and Keytel et al.'s (2005) models.

5.3 Method

This study is comprised of one experiment that involved a graded submaximal exercise (i.e., a step-test), and a second that involved actual silvicultural work (regeneration release). Two data sets were developed: a learning and test set (Figure 5-1). The learning data set obtained from participants performing a step-test was used to develop the proposed ANFIS prediction model. The test data set obtained from forest workers who performed a step-test prior to work in the morning, and then performed their regular workday activities, was used to assess the ANFIS prediction model and compare it with other methods.

5.3.1 Participants

Fifty-eight healthy men aged from 21 to 64 years participated in the research. Fifty participants (22 pre-commercial thinners from various areas in the Province of Quebec and 28 staff and students from Polytechnique Montreal) constituted the learning data set participants, and eight regeneration release workers constituted the test data set participants (Table 5.1). Participants had to pass the pre-activity readiness questionnaire (PAR-Q) before being accepted for the study (Chisholm et al., 1975; Shephard, 1988). No participants were competitive athletes and none regularly used medication. The study was approved by the Human Research Ethics Committee of Polytechnique Montréal. All participants signed a written informed consent form prior to partaking in the study.

Table 5.1: Participants' physical characteristics

Characteristics	Learning Set (n=50)		Test Set (n=8)	
	Mean (SD)	**[Range]**	**Mean (SD)**	**[Range]**
Age	46.8 (11.1)	[21-64]	24.6 (2.4)	[21-28]
Weight (kg)	77.6 (11.6)	[53.5-104.3]	75 (12.9)	[57.4-99.8]
Height (cm)	174 (7)	[156.9-187.9]	175 (5)	[167-182]
BMI ($kg.m^{-2}$)	25.6 (3)	[19-32.6]	24.4 (3.2)	[20.6-30.1]
HR_{rest} (bpm)	67.2 (10.2)	[47.7-86.7]	70.2 (13.6)	[50.5-88.5]

Note. SD: standard deviation; BMI: body mass index ($kg.m^{-2}$); HR_{rest}: resting heart rate (bpm).

5.3.2 Procedure

5.3.2.1 Learning data collection

The 50 learning data set participants performed the Meyer and Flenghi (1995) step-test either during the day in a laboratory (for the 28 university staff and students) or in the morning close to the work field prior to beginning the day's work (for the 22 pre-commercial thinners). This step-test has been validated against other graded submaximal exertion tests (Meyer and Flenghi, 1995) and against a maximal treadmill test (Imbeau et al., 2009). It has the following advantages: simple, cost-effective, and practical, it can be implemented safely without imposing high cardiac strain, particularly for older and less active individuals. An additional advantage is that step frequency (15 steps per min paced with a metronome) is sufficiently low for any worker to be able to keep pace at all four step heights, for superior overall test precision and robustness. Imbeau et al. (2010) demonstrated that the highest exertion level on this test reached by a forest workers group corresponded well to the exertion generally measured during typical regeneration release work. A detailed description of the Meyer and Flenghi step-test was provided in Chapter 4. The participant's heart rate was continuously measured and monitored during the test using a heart rate monitor (Polar Electro T-61 coded). Oxygen consumption was continuously measured using a portable oximeter (Cosmed Fitmate PRO). The learning data set included VO_2-HR measurements collected at rest and for each step height of the step-test, as well as individual participants' physical characteristics (age, weight, height, BMI, and HR_{rest}). The learning data set included 1050 data samples, of which 588 samples (28 participants × 21 min) were obtained from the university staff and students and 462 samples (22 participants × 21 min) from the pre-commercial thinners.

5.3.2.2 Test data collection

The eight forest workers first performed the Meyer and Flenghi step-test in the morning shortly after their arrival at the worksite, close to the patch that had to be cleared during the day. Heart rate and oxygen consumption were continuously measured using the Polar Electro and Cosmed Fitmate PRO instruments. The worker's HR_{rest} was determined during the 5-minute rest preceding the test. After completing the step-test, the worker was released and began his regular workday (of regeneration release work), which involved variable workload intensities as a result of varied work conditions (e.g., sloping terrain, field obstacles, vegetation density, and stem diameters to be cut) (Toupin et al., 2007). Meyer and Flenghi (1995) showed that the step-test can be administrated at the beginning of a workday without compromising a participant's ability to perform physical work throughout the work shift due to undue fatigue. The worker's heart rate was continuously measured throughout the day using the Polar Electro, while oxygen consumption was measured using the Cosmed Fitmate PRO for an average duration of 37 minutes (range: 34 to 53 min) around mid-morning. The Cosmed Fitmate PRO had this time limit, since it was deemed uncomfortable by the workers. The field VO_2 measurements provided a means to validate the energy expenditure estimates produced by the different heart rate based models. The test data set included VO_2-HR measurements collected during the early morning step-test and during the workday, as well as workers' physical characteristics (age, weight, height, BMI, and HR_{rest}). The sample size of the test set was 464 data samples, of which 168 samples (8 participants × 21 min) were obtained during the field step-test and 296 samples (8 participants × 37 min) were obtained during regeneration release work activities. The HR data collected during work were corrected by one of the authors using the method proposed by Vogt et al. (1970, 1973) to remove the thermal component (or thermal pulse) from the raw field-measured HR data. This HR increase is related to an increase in body core temperature because of hot working conditions (Rowell, 1986; Kampmann et al., 2001), and it may contribute to a significant VO_2 overestimation when a participant's VO_2-HR relationship from the morning step-test is used to estimate work VO_2 from uncorrected HR measurements in the field.

5.3.3 Model development

Three ANFIS modules were built for the estimation of the Flex-HR parameters using the learning data set, namely ANFIS module 1 (associated with VO_2 rest), ANFIS module 2 (associated with the Flex point), and ANFIS module 3 (associated with the slope and intercept of the linear VO_2-HR curve) (Figure 5-1). The development of each module involved three steps: input screening, model selection, and final model building. For the simultaneous input screening and model selection, the learning set was split into two sets (training and validation) (Ripley, 1996). The training data set was used for developing models incorporating different sets of input variables, while the validation data set was used to determine the optimal set of input variables. The estimated Flex-HR parameters formed individuals' calibration curves (ANFIS prediction model), which were used to estimate VO_2. The estimated Flex-HR parameters were then compared to those estimated by the standard Flex-HR method and by Rennie et al.'s model using workers' step-test data from the test data set. In addition, VO_2 estimates from the ANFIS prediction model were compared to the measured VO_2, and estimates from the standard Flex-HR method, Rennie et al.'s model, and Kytel et al.'s model using the VO_2-HR work data from the test data set. The fuzzy logic toolbox provided in MATLAB (version 7.5.0) was used to develop the fuzzy models.

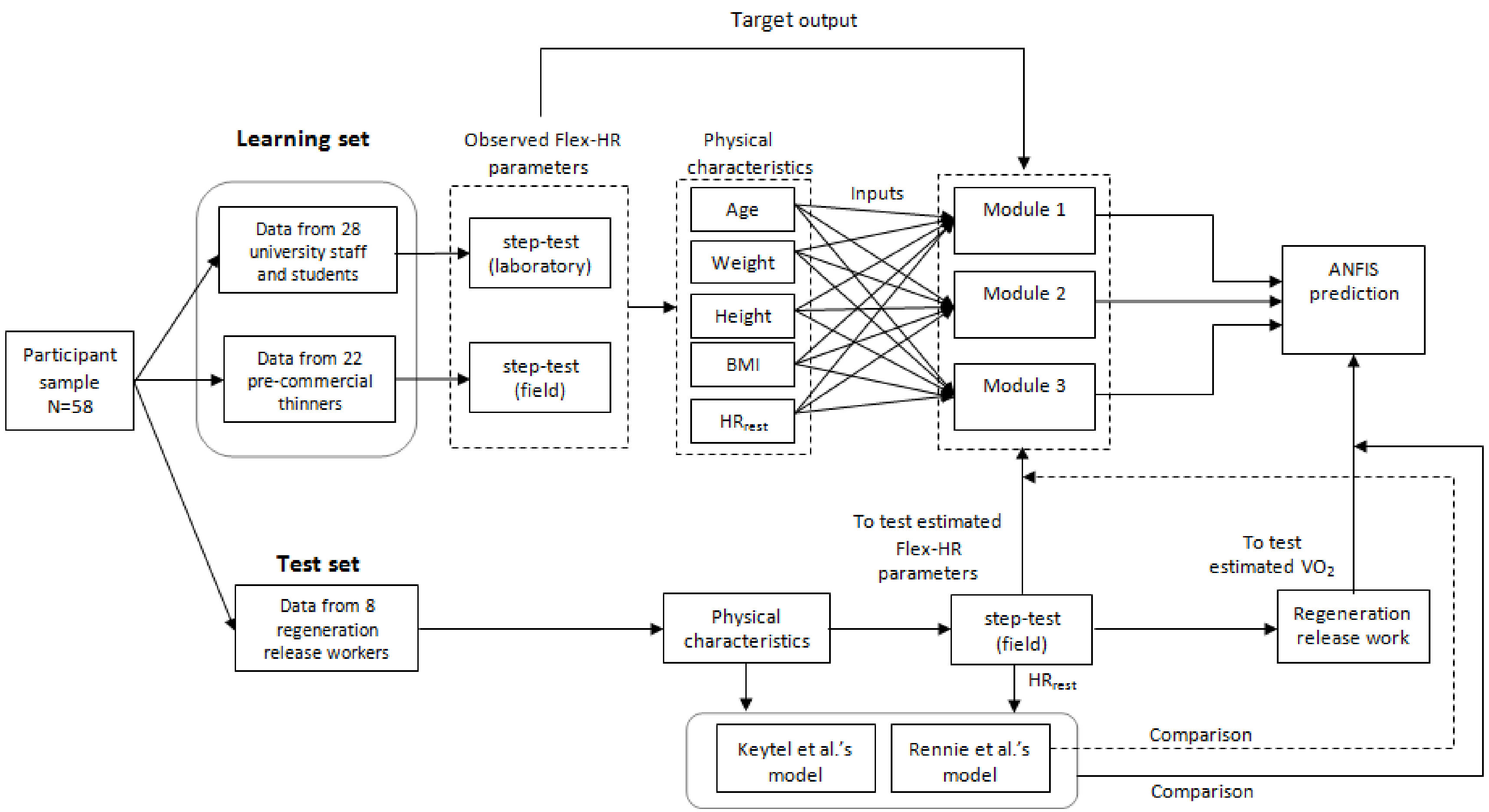

Figure 5-1: Schematic description of the study

5.3.3.1 Simultaneous input screening and model selection

The first step in developing the ANFIS model was to identify the significant input variables associated with each ANFIS module. In this study, five input variables were considered in the following order: age, weight, height, BMI, and HR_{rest}. The following sets were defined as follows: $\{i\}$ is the set of input variables after removing the i^{th} input variable; $\{i, j\}$ is the set of input variables after removing the i^{th} and j^{th} input variables; $\{i, j, k\}$ is the set of input variables after removing the i^{th}, j^{th} and k^{th} input variables (where $i, j, k = 1, 2, 3, 4, 5$ and $i \neq j \neq k$). Candidate sets of input variables were determined for each ANFIS module using the backward selection method (Chiu, 1996). The 10-fold cross validation method was simultaneously used for accurate performance assessment since it has been found superior to other methods (e.g., holdout, bootstrap and leave-one-out cross validation methods) in determining the generalization error in model selection problems (Breiman and Spector, 1992; Kohavi, 1995; Molinaro et al., 2005). A description of the simultaneous use of the backward selection method and 10-fold cross validation is provided in Appendix F.

As demonstrated by Rennie et al. (2001), a strong negative correlation (0.94) was found between the slope and the intercept of the linear curve. Therefore, due to the dependency between the slope and the intercept, module 3 was used for the estimation of both parameters in this study. Candidate sets of input variables associated with the ANFIS modules are presented in Table 5.2. Based on each candidate set, a fuzzy model was developed for each of the 10 partitions using the training data set associated with that partition. The optimal subtractive clustering parameters were determined using an enumerative search (Table 5.2). Figure 5-2 (a, b, and c) show the average performance (i.e., RMSE) (over all 10 partitions) of the fuzzy models incorporating different candidate sets for modules 1, 2, and 3, respectively, based on the validation data set. Key input variables associated with the ANFIS modules are presented in Table 5.2.

Table 5.2: Description of the development of ANFIS modules

ANFIS Modules	**Candidate sets**	**Clustering parameters**	**Significant input variables**
Module 1	{0},{1},{2},{3},{4},{5},{1,4},{2,3},{2,4},{2,5},{3,4},{3,5},{4,5},{1,2,4},{2,3,4},{2,4,5}	$r = 0.5$, $\eta = 1.1$, $\overline{\in} = 0.9$, $\underline{\in} = 0.7$	Age, weight, Height, HR_{rest}
Module 2	{0},{1},{2},{3},{4},{5},{1,3},{1,4},{2,3},{3,4},{3,5},{1,2,3},{1,3,4},{1,3,5},{2,3,4}	$r = 0.3$, $\eta = 1.1$, $\overline{\in} = 0.9$, $\underline{\in} = 0.7$	Weight, BMI, HR_{rest}
Module 3	{0},{1},{2},{3},{4},{5}	$r = 0.3$, $\eta = 0.7$, $\overline{\in} = 0.9$, $\underline{\in} = 0.9$	Age, weight, height, BMI, HR_{rest}

Note. r: cluster radius; η: squash factor (penalty radius/cluster radius); $\overline{\in}$: Accept ratio; $\underline{\in}$: reject ratio; {i}: set of input variables after removing the i^{th} input variable (where i = 1, 2, 3, 4, and 5 corresponds to age, weight, height, BMI, and HR_{rest}, respectively); {i, j}: set of input variables after removing the i^{th} and j^{th} input variables (where i, j = 1, 2, 3, 4, and 5 correspond to age, weight, height, BMI, and HR_{rest}, respectively and $i \neq j$); {i, j, k}: set of input variables after removing the i^{th}, j^{th} and k^{th} input variables (where i, j, k = 1, 2, 3, 4, and 5 correspond to age, weight, height, BMI, and HR_{rest}, respectively and $i \neq j \neq k$).

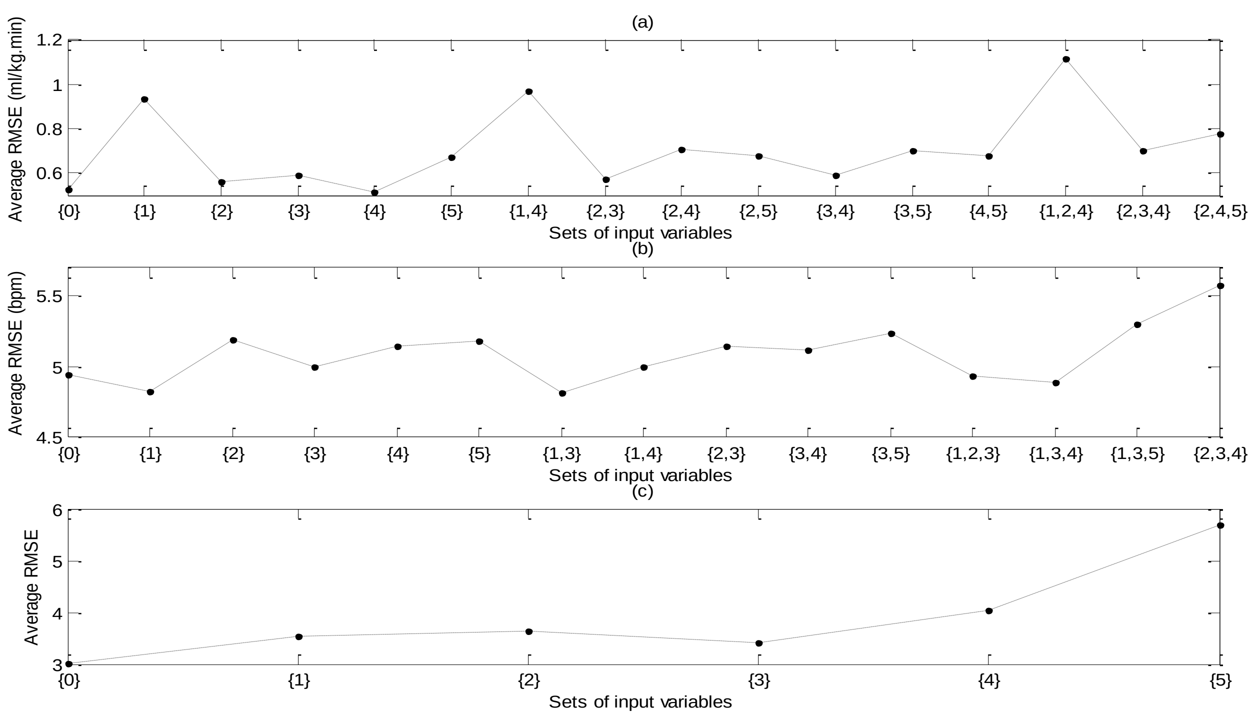

Figure 5-2: Average performance of fuzzy models associated with different sets of inputs for: (a) module 1; (b) module 2; and (c) module 3

5.3.3.2 Final model building

After identifying the sets of significant input variables, each ANFIS module was trained with the learning data set using the back-propagation gradient descent method combined with the least squares method for 20 epochs (Fuzzy logic toolbox, MATLAB version 7.5.0). The final structure of the ANFIS modules is presented in Table 5.3. Appendix G describes the structure of the three ANFIS modules with associated membership functions and parameters.

Table 5.3: Description of the final structure of ANFIS modules

ANFIS module	**No. Of fuzzy IF-THEN rules**	**No. Of mf**	**Input variable**	**No. Of modifiable parameters**	
				Antecedent	**Consequent**
Module 1	2	2	Age, weight, height, and HR_{rest}	16	10
Module 2	5	5	Weight, BMI, and HR_{rest}	30	20
Module 3	2	2	Age, weight, height, BMI, and HR_{rest}	20	24

Note. mf: Gaussian membership function assigned to each input variable; Antecedent: IF part of a fuzzy rule; Consequent: THEN part of a fuzzy rule; BMI: body mass index ($kg.m^{-2}$); HR_{rest}: resting heart rate (bpm).

5.3.4 Estimation models for comparison

Three VO_2 estimation methods were used in this study for comparison with the developed ANFIS prediction model. The standard Flex-HR method uses individual VO_2-HR measurements during the Meyer and Flenghi step-test to determine the Flex-HR parameters so as to establish a participant's calibration curve. The Flex-HR parameters were determined in accordance with Spurr et al. (1988) and Ceesay et al. (1989). In addition, two general VO_2 estimation models proposed by Rennie et al. (2001) and Keytel et al. (2005) were considered in this study. The former model includes three linear prediction equations developed using regression analysis for estimating the Flex-HR parameters:

$$Resting\ energy\ expenditure = -1.1 \times Gender + 0.04 \times Weight + 0.02 \times HR_{rest} \quad (1)$$

$$Flex\ point = 1.7 \times Gender + 0.23 \times BMI + 0.93 \times HR_{rest} \quad (2)$$

$$Slope = -0.12 \times Gender + 0.002 \times Age + 0.003 \times Weight \quad (3)$$

The input variable *Gender* equals 1 for male and 2 for female. The units for resting energy expenditure, weight, HR_{rest}, Flex point, BMI and age are kJ/min, kg, bpm, bpm, kg/m^2 and years, respectively. The intercept of the linear function describing the VO_2-HR relationship above the Flex point is estimated using regression analysis on the computed slope (Eq. (3)). On the other hand, Keytel et al.'s model consists of one linear equation to estimate EE using mixed-models analyses:

$$EE = Gender \times (-55.0969 + 0.6309 \times HR + 0.1988 \times Weight + 0.2017 \times Age) + (1 - Gender) \times (-20.4022 + 0.4472 \times HR - 0.1263 \times Weight + 0.074 \times Age) \quad (4)$$

The input variable *Gender* equals 1 for male and 0 for female.

5.3.5 Model testing and comparisons

Part of the test data set, which is the morning step-test data collected from the eight forest workers, was used to determine the parameters of the standard Flex-HR method (observed parameters) and to develop the associated individual calibration curves. The observed parameters were then compared with the estimates from the three ANFIS modules, and Rennie et al.'s model (Eqs. (1), (2), and (3)). Next, VO_2 estimates from the ANFIS prediction model were compared with VO_2 measurements, as well as with VO_2 estimates from the standard Flex-HR (observed parameters), Rennie et al.'s and Keytel et al.'s (Eq. (4)) models using the rest of the test data set, which is the eight workers' data collected during the workday. HR data measured during work constituted the main input into the various models so as to produce VO_2 estimates (ANFIS prediction, standard Flex-HR from observed parameters, Rennie et al.'s and Keytel et al.'s models). Comparisons were made throughout the HR range, as well as for three HR categories: very light work: <80 bpm; light work: 80-100 bpm; and moderate to heavy work: >100bpm (Smolander et al., 2008).

5.3.6 Statistical analyses

The performance of the three ANFIS modules in estimating the Flex-HR parameters was assessed and compared with other models using the mean absolute error (MAE) and mean absolute percentage error (MAPE). Similarly, MAE and MAPE were used to assess and compare the performance of the ANFIS prediction model in estimating VO_2 against the measured VO_2 values and the other estimation models. Student's two-tailed t-test for paired observations was used to test for differences among the values to be compared. A threshold of $p < 0.05$ was considered statistically significant. Limits of agreement (LOA) between the measured VO_2 values and the values estimated by the ANFIS prediction model, the standard Flex-HR, Rennie et al.'s and Keytel et al.'s models, were determined using the Bland-Altman plot to examine the accuracy of the estimation models (Bland and Altman, 1986). Moreover, the coefficient of variation (CV= standard deviation/sample mean*100) was used to assess the relative precision of all models.

5.4 Results

Overall, 1514 minutes were analyzed (1218 min during the step-tests and 296 min during regeneration release work). The mean of the individual average HR was 86 (range 47-142) bpm during the step-tests and 104.4 (range 49-146) bpm during the regeneration release work. The largest portion of HR data (43%) from all participants during the step-tests was below 80 bpm, followed by 33% between 80 and 100 bpm, and 24% above 100 bpm. However, the largest portion of HR data (59%) during regeneration release work was above 100 bpm, followed by 23% below 80 bpm, and 18% between 80 and 100 bpm.

5.4.1 Estimated Flex-HR parameters

Table 5.4 presents the average observed Flex-HR parameters and estimated parameters using the three ANFIS modules and Rennie et al.'s model. The respective ANFIS modules yielded significantly better performance than Rennie et al.'s model in terms of percent difference vs observed value for each parameter, MAE and MAPE. The paired t-test indicated no significant differences in estimating the observed parameters using the three ANFIS modules, whereas Rennie et al.'s model yielded significantly different parameter estimates ($p<0.001$). Figure 5-3 shows the performance of the three ANFIS modules as well as that of Rennie et al.'s model in estimating the observed parameters of the standard Flex-HR method with the morning step-test data obtained from the eight workers.

Table 5.4: Average estimated Flex-HR parameters and estimation errors associated with the three ANFIS modules (n=8)

Flex-HR parameters	**Observed**	**ANFIS prediction**			**Rennie et al.'s models**		
	$\bar{x}\,(SD)$	$\bar{x}\,(SD)$	**MAE**	**MAPE**	$\bar{x}\,(SD)$	**MAE**	**MAPE**
VO_2 rest (ml/kg.min)	5.69 (0.58)	5.33 (0.5) 6.3%[1]	0.57	9.7%	3.3 (0.41) 42.0%[1] ***	2.38	41.4%
Flex point (bpm)	81.38 (12.22)	82.17 (11.6) 1.0%[1]	1.65	2.1%	72.62 (12.28) 10.8%[1] ***	8.75	10.9%
Slope (ml/kg.min/bpm)	0.36 (0.09)	0.35 (0.06) 2.8%[1]	0.05	15.4%	0.15 (0.04) 58%[1] ***	0.2	55.2%
Intercept (ml/kg.min)	-17.81 (7)	-17.58 (5.1) 1.3%[1]	3.18	29.6%	-1.83 (3.4) 89.7%[1] ***	15.98	86.0%

Note. $\bar{x}\,(SD)$: average (standard deviation) values over the 8 participants; MAE: mean absolute error; MAPE: mean absolute percentage error; ***p < 0.001 significantly different from the measured VO_2; [1] % difference vs Observed.

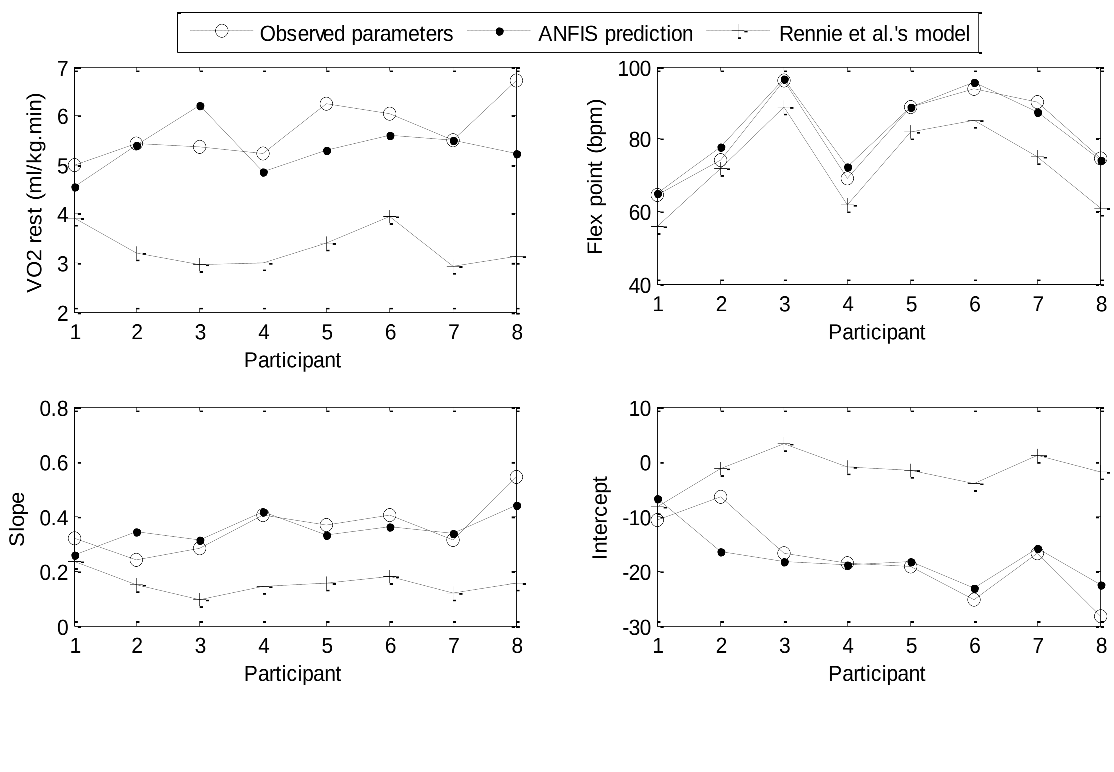

Figure 5-3: The performance of ANFIS modules in estimating the Flex-HR parameters

5.4.2 Estimated oxygen consumption

Table 5.5 summarizes the results obtained for each VO_2 estimation method based on the data obtained from the eight workers during actual work activities. It shows the mean of all participants' average VO_2 estimation per model, as well as the corresponding mean MAE and MAPE for the whole HR range and separately for the three HR categories. In addition, it includes a ranking of different VO_2 estimation models. Results show that the standard Flex-HR, ANFIS prediction and Rennie et al.'s models underestimated measured VO_2 with overall mean differences of 0.69, 1.12 and 6.18 ml/kg.min, respectively, whereas Keytel et al.'s model overestimated measured VO_2 with an overall mean difference of 0.92 ml/kg.min. In addition, measured VO_2 values were underestimated by all models in the lower HR range. The VO_2 relative difference associated with the lower HR range was smallest with the standard Flex-HR method (8.9%) and largest with Rennie et al.'s model (25.1%). In the medium HR range, the smallest relative difference was obtained with ANFIS prediction model (4.8%), whereas the highest relative difference was obtained with Keytel et al.'s model (12%). The relative difference in the higher HR range was smallest with Keytel et al.'s model (2.5%) and highest with Rennie et al.'s model (37.2%).

In terms of model estimation errors, the standard Flex-HR method yielded the most accurate VO_2 estimates, followed by the ANFIS prediction model, Rennie et al.'s and Keytel et al.'s models throughout the overall HR range and in different HR ranges. Rennie et al.'s model outperformed Keytel et al.'s in the lower and medium HR ranges, whereas the latter had smaller relative estimation errors in the higher HR range. The paired t-test showed no significant difference between the measured VO_2 values and those estimated by the ANFIS prediction model throughout the entire HR range and separately in different HR ranges. On the other hand, the standard Flex-HR method significantly underestimated the measured VO_2 in the overall HR range and in the higher HR range (Table 5.5). Rennie et al.'s model significantly underestimated the measured VO_2 in the overall, lower and higher HR ranges. Keytel et al.'s model significantly overestimated the measured VO_2 in the higher HR range.

Table 5.5: Average mean VO_2 and estimation errors associated with all developed models throughout HR range and in different HR intervals (n=8)

HR range (bpm)	**Measured VO_2 (ml/kg.min)**	**Standard Flex-HR**			**ANFIS prediction**			**Rennie et al.'s model**			**Keytel et al.'s model**		
		$\widehat{VO}_2$	MAE	MAPE	$\widehat{VO}_2$	MAE	MAPE	$\widehat{VO}_2$	MAE	MAPE	$\widehat{VO}_2$	MAE	MAPE
Overall HR range (n=8)	19.1	18.41 [0.69] 3.6% r =.96 {16.17} *	2.33 (1)	16.27 (1)	17.98 [1.12] 5.9% r =.91 {16.58}	3.0 (2)	20.06 (2)	12.92 [6.18] 32.4% r =.87 {18.53} **	6.95 (4)	36.05 (3)	20.02 [-0.92] 4.8% r =.79 {21.63}	5.99 (3)	44.87 (4)
Lower range HR<80	7.09	6.46 [0.63] 8.9% {20.5}	1.58 (1)	21.27 (1)	6.0 [1.1] 15.5% {23.32}	1.79 (2)	23.26 (2)	5.31 [1.78] 25.1% {33.84} **	2.44 (3)	35.52 (3)	5.91 [1.18] 16.64% {47.31}	3.18 (4)	47.1 (4)
Medium range 80≤HR≤100	13.05	14.07 [-1] 7.8% {23.62}	2.52 (1)	25.46 (1)	13.67 [-0.6] 4.8% {23.04}	2.8 (2)	27.17 (2)	11.51 [1.54] 11.8% {19.64}	4.45 (3)	36.59 (3)	14.62 [-1.57] 12% {17.76}	5.32 (4)	51.96 (4)
Higher range HR>100	26.84	25.61 [1.23] 4.6% {8.64} *	2.53 (1)	10.06 (1)	25 [1.84] 6.9% {8.9}	4 (2)	15.76 (2)	16.85 [10] 37.2% {5.77} ***	10.1 (4)	35.57 (4)	27.51 [-0.67] 2.5% {9.64} **	7 (3)	30.75 (3)

Note. MAE: mean absolute error (ml/kg.min); MAPE: mean absolute percentage error (%); [ ]: mean difference of VO_2 (ml/kg.min); %: percentage difference of VO_2. (*i*): ranking of VO_2 estimation methods based on estimation errors, where *i* = 1, 2, 3 or 4; r: correlation coefficient; { }: coefficient of variation (%); *p < 0.05, **p < 0.01 and ***p < 0.001 significantly different from the measured VO_2.

The Bland-Altman plot in Figure 5-4 depicts the limits of agreement (LOA) between measured and estimated (i.e., by the standard Flex-HR, ANFIS prediction, Rennie et al.'s and Keytel et al.'s models) VO_2 values. The difference between the measured and estimated VO_2 was smallest: in the medium HR range with the standard Flex-HR and ANFIS prediction models, in the lower HR range with Rennie et al.'s model, and in the higher HR range with Keytel et al.'s model. On the other hand, the largest bias was: in the lower HR range with Keytel et al.'s model, and in the higher HR range with other models. Results show more compact VO_2 estimates by all VO_2 estimation models in the lower HR range reflecting lower standard deviations (Table 5.6). Moreover, the LOA associated with the ANFIS prediction and Keytel et al.'s models get narrower as work intensity decreases. However, for the standard Flex-HR and Rennie et al.'s models, the LOA are widest in the medium HR range.

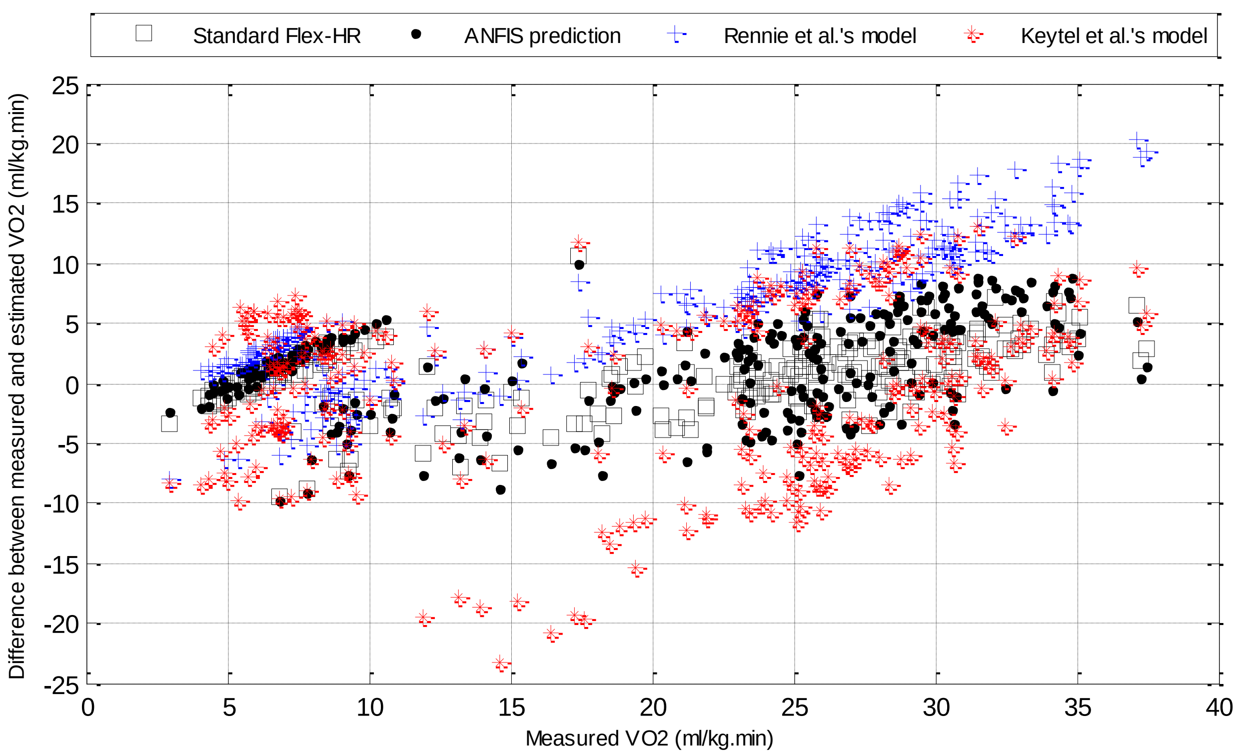

Figure 5-4: Bland-Altman plot to test the agreement between measured and estimated VO_2 values using VO_2-HR measurements during regeneration release work (n=8)

Table 5.6: Bias and LOA associated with VO_2 estimation models with respect to measured VO_2

HR range (bpm)	Models	Bias (ml/kg.min)	SD (ml/kg.min)	Limits of agreement (LOA)	
				Lower limit (ml/kg.min)	Upper limit (ml/kg.min)
Overall HR range (n=8)	Standard Flex-HR	0.8	2.7	-4.6	6.1
	ANFIS prediction	1.2	3.5	-5.7	8.1
	Rennie et al.	6.5	5.8	-4.8	17.8
	Keytel et al.	-0.5	7.0	-14.2	13.3
Lower range HR<80	Standard Flex-HR	0.8	2.2	-3.5	5.1
	ANFIS prediction	1.5	2.2	-2.7	5.8
	Rennie et al.	1.7	2.2	-2.7	6.1
	Keytel et al.	3.0	2.9	-2.8	8.8
Medium range 80≤HR≤100	Standard Flex-HR	-0.4	2.9	-6.1	5.2
	ANFIS prediction	0.3	3.7	-6.9	7.5
	Rennie et al.	2.6	6.0	-9.1	14.2
	Keytel et al.	-1.8	6.4	-14.4	10.8
Higher range HR>100	Standard Flex-HR	1.1	2.7	-4.2	6.5
	ANFIS prediction	1.6	4.0	-6.2	9.4
	Rennie et al.	9.6	4.5	0.7	18.4
	Keytel et al.	-1.4	7.8	-16.8	13.9

Note. HR: heart rate (bpm); Bias: average difference between measured and estimated VO_2 values (ml/kg.min); SD: standard deviation of the difference between measured and estimated VO_2 values (ml/kg.min); LOA: limits of agreement between the measured and the estimated VO_2 values (ml/kg.min).

5.5 Discussion

The analysis of the estimated Flex-HR parameters by the three ANFIS modules did not only show a similarity to the observed Flex-HR parameters, but also a significant reduction in estimation errors when compared to Rennie et al.'s model. For example, a reduction in MAE of approximately 76%, 80%, 75%, and 80% was reported when estimating VO_2 rest, Flex point, slope, and intercept, respectively. The ANFIS prediction model yielded more accurate VO_2 estimates than Rennie et al.'s and Keytel et al.'s models in the overall HR range and separately in different HR ranges, as indicated in Table 5.5. The results show that the proposed model produces percentage differences at lower HR (15.5%), medium (4.8%) and higher (6.9%) HR ranges, that are comparable with the ±10% figure generally expected when estimating the metabolic rate based on HR measurements using individual calibration methods (ISO-8996, 2004). The paired t-test indicated a significant difference between the measured and estimated VO_2 by the standard Flex-HR method in the overall and higher HR ranges, which was not the case for the ANFIS prediction model. A possible explanation for this result is the very small standard error of the differences between the measured VO_2 values and those estimated by the standard Flex-HR method. As a result, a large t-ratio (2.58 throughout the entire HR range and 2.49 in the higher HR range) was obtained, corresponding to a small p-value (0.038 over the entire HR range and 0.042 in the higher HR range). Despite this result, a closer look at the 95% confidence interval (CI) of the true mean difference between the measured and estimated VO_2 reveals that both CI ends (CI: 0.05–1.3 ml/kg.min over the entire HR range and 0.06–2.2 ml/kg.min in the higher HR range) represent a trivial difference. Hence, one can conclude that although the difference between the measured VO_2 values and those estimated by the standard Flex-HR method is statistically significant, practically speaking, it is relatively small. The fact that the ANFIS prediction model provides better prediction in the lower and medium HR ranges (than the higher HR range) indicates its ability to deal with the nonlinearity and uncertainty between VO_2 and HR at low work intensity. This finding is also supported by the comparable LOA associated with the ANFIS prediction (-2.7, 5.8) and with the standard Flex-HR (-3.5, 5.1) models in the lower HR range. The agreement between the measured VO_2 values and that estimated by the ANFIS prediction model throughout the entire HR range suggests the potential of the developed model to be a very efficient replacement for the standard Flex-HR method, since it does not require the collection of submaximal exercise data and the construction of an individual's Flex-HR calibration curve. The developed model can be used directly to assess VO_2 from HR measured during work provided that age, weight, height, and HR_{rest} of the participant are known. Although the standard Flex-HR method provides more accurate VO_2 estimates, this precision can only be achieved at the expense of a greatly increased cost of implementation.

The model performance statistics from this study are in agreement with the recent literature. In 2001, Rennie and colleagues showed that EE estimated using their proposed models correlated with measured EE with a correlation coefficient of 0.82 ($p<0.01$) over the full HR range. Moreover, Keytel et al. (2005) found that their proposed model correlated with the measured EE values with a correlation coefficient of 0.77 ($p<0.0001$). These results agree with our findings for Rennie et al.'s model ($r=0.87$, $p<0.0001$) and Keytel et al.'s model ($r=0.79$, $p<0.0001$). Furthermore, the correlation coefficient associated with the ANFIS prediction model ($r=0.91$, $p<0.0001$) was found to be higher than that of Rennie et al.'s and Keytel et al.'s models, but lower than the standard Flex-HR method ($r=0.96$, $p<0.0001$). Firstbeat Technologies (2005) proposed a general neural network-based method for VO_2 estimation based on both HR and heart rate variability. Pulkkinen et al. (2004) found this method to yield a MAE of approximately 2.5 ml/kg.min, which is comparable to our findings with the ANFIS prediction model (MAE = 3 ml/kg.min, range = 1.8 to 4 ml/kg.min). In 2007, Firstbeat Technologies reported a 13.5% MAPE for the standard Flex-HR method, which is coherent with our finding (MAPE = 16.3%, range = 10.1% to 25.5%). They also reported a 22% MAPE for Rennie et al.'s model, which is lower than our findings (MAPE = 36.1%, range = 35.5% to 36.6%). This difference is likely due to the use of field-collected data (vs laboratory data) for model evaluation and comparison in this study. The standard Flex-HR method has been reported to yield a coefficient of variation (CV) of 16.7% (Ceesay et al., 1989) and 18.6% (Spurr et al., 1988) over the full HR range, which is comparable with our finding (CV = 16.2%, range = 8.6% to 23.6%) (Table 5.5). Moreover, our results indicated that the ANFIS prediction model proposed here yielded a CV of 16.6% (range = 8.9% to 23.3%), indicating a relative precision comparable to that of the standard Flex-HR method.

Although adequate knowledge of MATLAB was required to develop the ANFIS prediction model, it has been implemented in Excel (Appendix H) so that researchers and practitioners can easily use it as a decision support tool. (A complete Excel file implementing the model can be obtained by contacting the first author of the paper). Unlike other general calibration models, the ANFIS prediction model treats different portions of the VO_2-HR relationship by using three ANFIS modules, therefore using more information for each. For example, ANFIS module 1 provides an accurate estimate of VO_2 rest, which indicates daily sedentary energy expenditure, with an estimation error of approximately 0.57 ml/kg.min. HR can be monitored during sitting rest, and the average of recorded HR_{rest} values —in addition to age, weight, and height— can be entered into the ANFIS module 1 rule-base to obtain an estimate of VO_2 rest. The ANFIS module 1 has the potential to be implemented in a wide range of applications that require estimations of an individual's daily sedentary energy expenditure, such as in sport and health centers to establish dietary intake and weight-loss programs (Hofsteenge et al., 2010) and in medical centers and hospitals to determine patients caloric demand and thus their nutritive needs (Schwartz, 1998; Hart et al., 2002). On the other hand, determining the Flex point with ANFIS module 2 helps to distinguish between energy expenditure during rest and activity (Livingstone et al., 1992). This may be useful in a wide range of applications particularly in the industry, since determining workers' Flex point may allow for better design of work-rest schedules. Although the ANFIS prediction model was tested with younger participants (test data set), the results demonstrate its performance to be comparable with the standard Flex-HR method. This indicates that the performance of the ANFIS prediction model would be expected to be higher if tested with older participants, since it was initially trained with data from older participants. Practitioners should be aware that the ANFIS prediction model will overestimate VO_2 when a significant thermal pulse is present. Hence, the HR thermal component (thermal pulse) must be removed prior to using the ANFIS model (Vogt et al. 1970, 1973). This raises the need to investigate the thermal stress impact on the ANFIS modules development. Further studies could include a larger number and variety of participants and a variety of actual work activities with different intensities for ANFIS modules training and validation.

5.6 Conclusion

The purpose of this study was to develop a simple and practical approach to estimating energy expenditure based on HR measurements that does not require individual submaximal graded exercise calibration test data. The proposed ANFIS prediction model stems from the standard Flex-HR method, which has been recognized as one of the most accurate methods for VO_2 estimation based on HR. This study shows the proposed ANFIS model to be quite accurate (<10%) in estimating measured VO_2, which strongly implies that it can replace the standard Flex-HR method, especially in work environments where one cannot afford to have each participant of a group targeted for study to take a graded exercise test. The proposed model does not only represent a new application of fuzzy logic for VO_2 estimation, but it can also be implemented as easily as the standard Flex-HR method due to recent significant advancements in software and computational methods.

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CHAPTER 6: ARTICLE 3 – CLASSIFYING WORK RATE FROM HEART RATE MEASUREMENTS USING AN ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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6.1 Abstract

In a new approach based on adaptive neuro-fuzzy inference systems (ANFIS), field heart rate measurements were used to classify work rate into four categories: very light, light, moderate, and heavy. Intersubject variability (physiological and physical differences) were considered. Twenty-eight participants performed Meyer and Flenghi's step-test and maximal treadmill test, during which heart rate and oxygen consumption were measured. Results indicated that heart rate monitoring (HR, HR_{max}, and HR_{rest}) and body weight are significant variables for classifying work rate. The ANFIS classifier showed superior sensitivity, specificity, and accuracy compared to current practice using established work rate categories based on percent heart rate reserve (%HRR), with an overall 29.6% difference in classification accuracy between the two methods, and good balance between sensitivity (90.7%, on average) and specificity (95.2%, on average). With its ease of implementation and variable measurement, the ANFIS classifier shows potential for widespread use by practitioners for work rate assessment.

Keywords: work rate; heart rate; adaptive neuro-fuzzy inference system (ANFIS)

6.2 Introduction

Despite the global trend towards mechanization, many industries, such as forestry, construction, and mining, still entail physically demanding labor. Excessive physical work demands are the main cause of undue fatigue, which affects workers and leads to lower work performance and quality (Abdelhamid, 1999). Studies have suggested that understanding the physical demands of work is key to protecting safety and health in the workplace and enhancing productivity (Brouha, 1967; The Eastman Kodak Company, 2004). Work physiology researchers have underscored the importance of assessing the physiological demands of physical activity, and have fostered the use of categorical scales to measure work rate (e.g., light, moderate, and heavy), with several applications, such as thermal stress assessment (ACGIH, 2009; ISO 11079, 2008). There are three main methods for classifying work rate (Table 6.1). The first is based on energy expenditure, which can be assessed indirectly by measuring oxygen consumption (VO_2) (Christensen, 1964; Hettinger, 1970; American Industrial Hygiene Association (AIHA), 1971; Astrand and Rodahl, 1986). This method is costly, invasive, and time-consuming, and it requires sophisticated equipment (Smolander et al., 2008). In the second method, work rate is classified based on variables that can be linearly related to oxygen consumption, such as heart rate (HR) (Grandjean, 1980). Although this method is considered one of the most practical and useful methods, HR monitoring alone lacks accuracy due to high intersubject variability (Melanson and Freedson, 1996; Valanou et al., 2006). A third method recommended by the U.S. Department of Health and Human Services (1996) is to use the relative oxygen consumption or percentage of maximal oxygen consumption ($\%VO_{2max}$) to classify work rate. This method has been demonstrated accurate and is considered the gold standard for classifying work rate (U.S. Department of Health and Human Services, 1996; Haskell and Pollock, 1996; Pollock et al., 1998). For practical applications, several studies have recommended using the percent heart rate reserve (%HRR) to estimate $\%VO_{2max}$ (Haskell and Pollock, 1996; Pollock et al., 1998; American College of Sports Medicine (ACSM), 2006). The %HRR is calculated by estimating the maximal heart rate (HR_{max}), widely computed as 220 – age (Fox et al., 1971; Londeree and Moeschberger, 1982; McArdle et al., 1996; Tanaka et al., 2001; Robergs and Landwehr, 2002).

Today, there is a need for practical and reliable field methods for assessing and classifying work rate. They should use easily measured physical and physiological variables, such as HR, and they should account for intersubject variability. They should also allow dealing with the uncertainty and vagueness inherent in the human physiological system and in various work environments. In recent years, a number of artificial intelligence (AI) techniques have been proposed as alternatives to conventional statistical methods (Kaya et al., 2003; Yildirim and Bayramoglu, 2006). One of the most effective AI techniques, particularly for nonlinear function approximation and pattern recognition (classification), is the adaptive neuro-fuzzy inference system (ANFIS). It combines the unique ability of fuzzy logic to make decisions in uncertain conditions with the learning and adaptive capabilities of artificial neural networks. ANFIS has consistently been demonstrated effective in solving classification problems, particularly in biomedical engineering (Güler and Übeyli, 2004, 2005; Übeyli and Güler, 2005a, 2005b). This study presents a new ANFIS-based approach to classifying work rate using HR and physical characteristics. To develop the model, four ANFIS models were trained, one to classify work rate in each of four categories: very light (VL), light (L), moderate (M), and heavy (H). The individual models were trained to obtain optimal accuracy in each of the four work rate categories, and the four models were then combined into an integrated ANFIS classifier that classifies work rate into the four categories.

Table 6.1: Norms for work rate classification

Assessment of work rate	**VO_2 (L/min)**		**EE (kcal/min)**	**EE (kcal/8hr)**		**HR (bpm)**			**$\%VO_{2max}$ or %HRR**
	Christensen (1964)	Astrand and Rodahl (1986)	AIHA (1971)	AIHA (1971)	Hettinger (1970)	Christensen (1964)	AIHA (1971)	Astrand and Rodahl (1986)	U.S. Department of Health and Human Services, (1996) and ACSM (2006)
Sitting	___	___	1.5	< 720	___	___	60 – 70	___	___
Very low (Very light)	0.25 – 0.3	___	1.6 – 2.5	768 – 1200	___	60 – 70	65 – 75	___	0 - 24
Low (Light)	0.5 – 1.0	< 0.5	2.5 – 5.0	1200 – 2400	< 1000	75 – 100	75 – 100	< 90	25 - 44
Moderate	1.0 – 1.5	0.5 – 1.0	5.0 – 7.5	2400 – 3600	1000 - 1600	100 – 125	100 – 125	90 – 110	45 - 59
High (Heavy)	1.5 – 2.0	1.0 – 1.5	7.5 – 10.0	3600 – 4800	1600 - 2000	125 – 150	125 – 150	110 – 130	60 - 85
Very high (Very heavy)	2.0 – 2.5	1.5 – 2.0	10.0 – 12.5	4800 – 6000	> 2000	150 – 175	150 – 180	130 – 150	> 85
Extremely high (Unduly heavy)	2.5 – 4.0	> 2.0	> 12.5	> 6000	___	> 175	> 180	150 - 170	___

Note. VO_2 (L/min) = oxygen consumption in liters per minute; EE (kcal/min) = energy expenditure in kilocalories per minute; EE (kcal/8hr) = energy expenditure in kilocalories per 8 hours; HR (bpm) = heart rate in beats per minute; $\%VO_{2max}$= percentage of maximal oxygen consumption; %HRR= percent heart rate reserve.

6.3 Methods

The integrated ANFIS classifier (hereinafter, the classifier) was developed from a laboratory study in which the participants performed a submaximal step-test and a maximal treadmill test. Part of the participants' data (approximately 70%) was used to develop the classifier and the remaining data were used to validate it and compare its performance to the current practice in work classification, which uses %HRR.

6.3.1 Participants

A total of 28 healthy men aged from 20 to 45 years participated in the study (Table 6.2). Participants had to pass the pre-activity readiness questionnaire (PAR-Q) before being accepted for the study (Chisholm et al., 1975; Shephard, 1988). No participants were competitive athletes, and none regularly used medication. The study was approved by the Human Research Ethics Committee of Polytechnique Montréal. All participants signed a written informed consent form prior to partaking in the study.

Table 6.2: Physical characteristics of the participants

Characteristics	**Training (N=20)**		**Test (N=8)**	
	Mean (SD)	**[Range]**	**Mean (SD)**	**[Range]**
Age (yr)	38.33 (8.42)	[21-46]	34 (8.15)	[28-45]
Body weight (kg)	76.57 (7.61)	[68.2-98.5]	83.61 (14.74)	[63.6-104.5]
Height (cm)	171.83 (2.64)	[167.8-173.5]	176.53 (7.3)	[170.2-187.9]
BMI ($kg.m^{-2}$)	24.37 (1.41)	[23.2-26.3]	26.68 (3.09)	[21.2-29.5]
HR_{max} (bpm)	181.67 (8.42)	[174-199]	186 (8.15)	[175-192]
HR_{rest} (bpm)	77.77 (13.29)	[64.3-86.3]	73.08 (7.11)	[66.8-86.8]
VO_{2max} ($ml.kg^{-1}.min^{-1}$)	37.92 (6.56)	[30-45]	40 (5.48)	[30-45]

6.3.2 Laboratory study

All participants performed the Meyer and Flenghi (1995) step-test, which has the following advantages: simple, cost-effective, and practical, it can be implemented safely without imposing high cardiac strain, particularly for older and less active individuals. Imbeau et al. (2010) demonstrated that the highest exertion level on this test reached by a group of forest workers corresponded well to the exertion generally measured during typical regeneration release work. This step-test has been validated against other graded submaximal exertion tests (Meyer and Flenghi, 1995) and against a maximal treadmill test (Imbeau et al., 2009). An additional advantage is that step frequency (15 steps per min paced with a metronome) is sufficiently low for any worker to be able to keep pace at all four step heights, for superior overall test precision and robustness. The equipment consists of a lightweight portable bench with a height-adjustable step (11.5, 21.5, 31.5, and 41.5 cm). After a 5-minute sitting rest to obtain the resting heart rate (HR_{rest}), participants were asked to stand in front of the bench for 2 minutes. The test started with the participant stepping onto and off the lowest step height for 3 minutes, followed by a short, 30-second standing rest in front of the bench while the experimenter increased the step height by sliding the step out of the lowest set of tracks and into the second-height tracks. This 3.5-minute cycle was then repeated for the three remaining step heights. The participant's heart rate (HR) was continuously measured and monitored during the test using a heart rate monitor (Polar Electro T-61 coded) to ensure it remained below 85% of the participant's age-predicted maximum heart rate (HR_{max}) (Fox et al., 1971). Whenever this point was reached, the test was terminated. The complete Meyer and Flenghi (1995) test lasted 21 minutes, after which participants took a sitting rest until heart rate returned to resting. Oxygen consumption (VO_2) and respiration or breath rate (BR) were continuously measured using a portable oximeter (Cosmed Fitmate PRO).

Participants also performed a maximal multistage treadmill test to determine maximal cardiorespiratory fitness (VO_{2max}) (Leger and Boucher, 1980). Imbeau et al. (2009) showed that the Meyer and Flenghi (1995) step-test administrated prior to the treadmill test does not affect the results on the latter when conducted in this sequence. This is coherent with the aim of Meyer and Flenghi (1995), who designed the test so as not to induce undue fatigue, which could place a worker at risk if the test were administrated at the beginning of a physical work shift. Participants' VO_2 was measured during the maximal treadmill test using a metabolic cart (MOXUS Metabolic System). Prior to the step and treadmill tests, the flowmeter of the Moxus metabolic cart was calibrated using a standard 3-liter syringe. The O_2 and CO_2 sensors were also calibrated against reference gases according to manufacturer's specifications. The dataset for this study included VO_2, HR, and BR measurements collected at rest and for each step height of the step-test, as well as individual participants' VO_{2max} determined during the maximal treadmill test.

6.3.3 ANFIS classifier model development

In general, to develop a classifier, data are clustered using a subtractive clustering algorithm, the clusters are converted to initial fuzzy rules, and the fuzzy rules are then optimized using ANFIS (Chiu, 1994, 1997). In this study, for the subtractive clustering, the data on all participants were first separated into groups according to their respective category (based on $\%VO_{2max}$) such that each group was associated with a work rate category (VL, L, M, or H). A data sample was represented by a vector in the input space (e.g., HR during activity, HR_{max}, HR_{rest}, and body weight). A clustering algorithm was then applied separately to all data samples belonging to each group to identify cluster centers, each of which was converted to a fuzzy rule for identifying the associated category (Appendix I). Each set of fuzzy rules forms an initial fuzzy inference system (FIS) associated with that category. In order to increase the classification accuracy of each FIS, the initial parameters of that FIS must be optimized. The need to automatically fine-tune the FIS parameters is the main motivation for incorporating artificial neural networks, and hence the development of an adaptive neuro-fuzzy inference system (ANFIS) for identifying each category. More details about ANFIS can be found in Güler and Übeyli (2004, 2005) and Yildiz et al. (2009).

In this study, a three-step approach was used to develop the classifier (Figure 6-1). First, significant input variables were selected using the whole dataset (for the 28 participants). Next, an ANFIS classifier was developed (with the selected input variables) using a training dataset of 20 randomly selected participants. This classifier was then tested using a test dataset for the remaining eight participants. Initially, 42 data samples were collected from each participant. However, since data quality (i.e., precisely belonging to a specific work rate category) is extremely important in classifier development, the raw data were refined by removing noise and redundancy. For instance, because the rest period at the beginning of the step-test (step 0) was considered well representative of the VL category, data collected in rest periods between steps and at the end of the step-test were removed. In addition, because they did not well represent the associated work rate, data collected just after rest periods (at the beginning and between steps of the step-test) were removed. Although participants were given specific instructions on how to perform the step-test, they sometimes found it difficult to remain calm in rest periods and maintain the correct pace in the different steps of the step-test, resulting in irrelevant data. Furthermore, some technical problems resulted in inaccurate measurements of HR and VO_2, such as a wet Polar Electro chest strap (due to sweat), a wet Cosmed Fitmate face mask (due to breathing), and sudden movement of the Cosmed Fitmate cable attached to the chest. Therefore, the final refined dataset consisted of 746 data samples, of which 496 constituted the training dataset and the remaining 250 constituted the test dataset. The refined dataset comprised 304 data samples in the VL category, 277 in the L category, 122 in the M category, and 43 in the H category. The classifier was developed using the fuzzy logic toolbox provided in MATLAB (version 7.5.0).

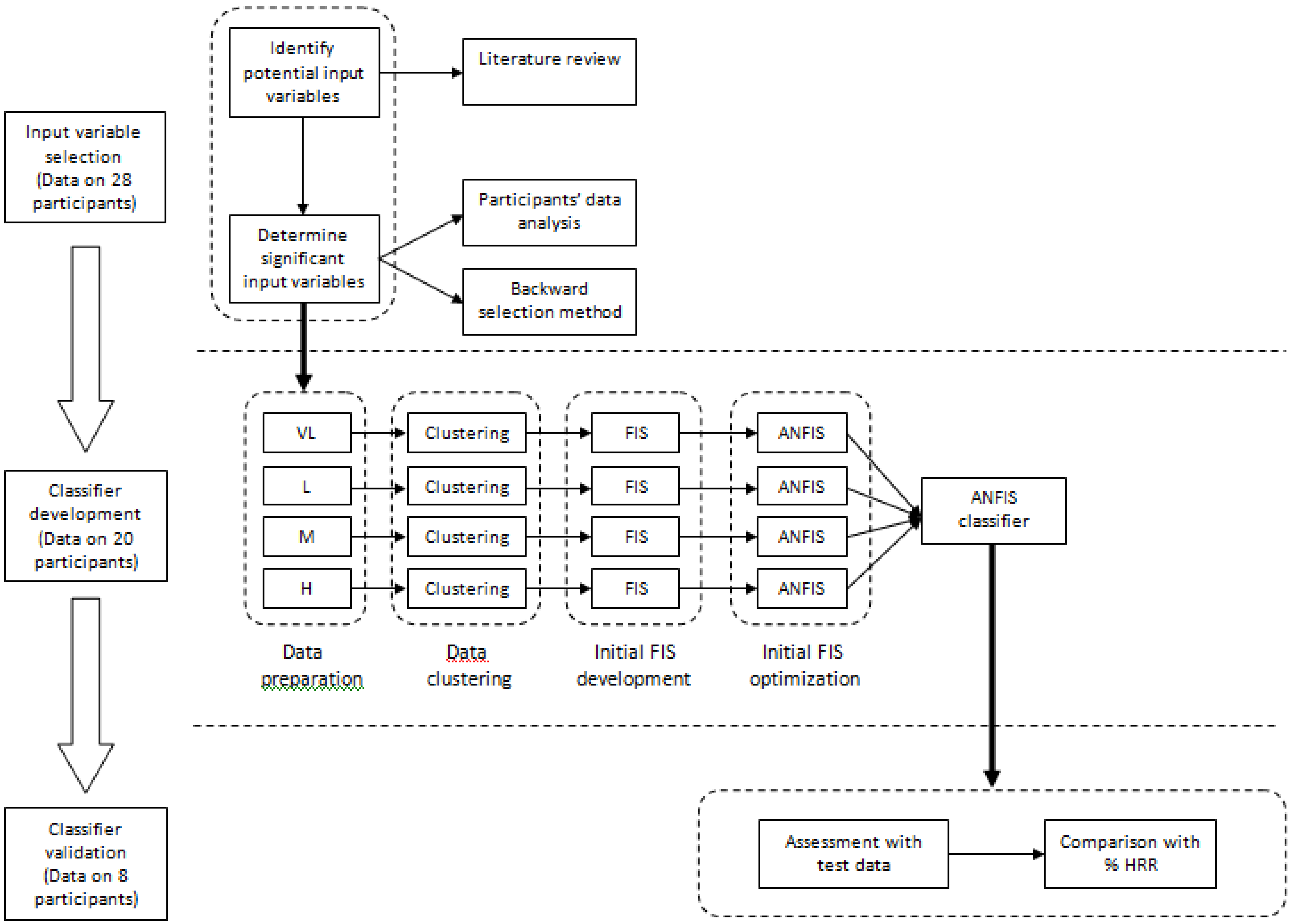

Figure 6-1: Development flow chart for the proposed ANFIS classifier

6.3.3.1 Selecting significant input variables

The first step in developing the ANFIS classifier was to identify the set of input variables that play a significant role in work rate classification. A set of all possible (potential) physical and physiological variables that affect the human physiological system was identified through a review of the scientific literature. Of these, significant variables were then determined by analyzing the participants' data using the backward selection procedure proposed by Chiu (1997).

From the literature review, eight potential input variables were identified: HR during activity (Christensen, 1964; AIHA, 1971; Astrand and Rodahl, 1986), HR_{max} (U.S. Department of Health and Human Services, 1996; ACSM, 2006), $\%HR_{max}$ (Panton et al., 1996; Dalleck and Kravitz, 2006; Binder et al., 2012), BR (Pulkkinen et al., 2004; Firstbeat Technologies Ltd., 2007), physical fitness (Skinner and Jankowski, 1974; Londeree and Ames, 1976; Rotstein and Meckel, 2000), which may be partly determined by HR_{rest} (Davis and Convertino, 1975; Panton et al., 1996), body weight, and BMI (Greenberg et al., 1995; Health Reviser, 2010; Hoeger and Hoeger, 2012). However, the results in the literature are contradictory on whether age has a significant (Panton et al., 1996) or negligible (Hellerstein, 1973; Franklin et al., 1980) impact on work rate assessment.

In the data analysis, the mean $\%VO_{2max}$ was computed for each step of the step-test using all participants' data (refined dataset), providing an overall work rate for each step. The effect of age on the $\%VO_{2max}$ variability within each step was then investigated in order to determine its relative importance. This was achieved by dividing the data into two groups based on age (older vs. young). Participants aged from 40 to 49 years were considered older, and those from 20 to 30 years were considered young (Heyward, 1998). An independent-sample t-test was performed to detect significant differences in step mean $\%VO_{2max}$ between the older and young groups. Results indicated no significant changes in $\%VO_{2max}$ between step-test steps. Age was therefore excluded from the set of potential input variables. The next step was to determine the significant physical and physiological variables using backward selection (Chiu, 1996) (Appendix J). An initial fuzzy classifier incorporating all potential input variables (HR during activity, HR_{max}, HR_{rest}, BR, BMI, and body weight) was generated, and each input variable and its associated antecedent clauses were then systematically removed from the rule-base in the initial fuzzy classifier. The performance measure associated with each resultant fuzzy classifier (after removing each input variable) was determined as overall classification accuracy (based on

$\%VO_{2max}$) in all steps of the step-test according to the test dataset. The highest classification accuracy was attained using the set $\%HR_{max}$ (i.e., HR during activity and HR_{max}), HR_{rest}, and body weight, which was therefore considered the set of significant input variables.

6.3.3.2 Developing the ANFIS classifier

Four ANFIS models corresponding to the four work rate categories of the step-test were trained using the back-propagation gradient descent method, and combined with the least squares method when the selected significant physiological and physical variables ($\%HR_{max}$, HR_{rest}, and body weight) were used as inputs. Each ANFIS model was trained to be more accurate for one work rate category over the others. The measured relative workloads ($\%VO_{2max}$) were assigned to the target outputs (VL, L, M, and H) such that each $\%VO_{2max}$ represents a work rate category as defined by the U.S. Department of Health and Human Services. The four ANFIS models were then combined to form the ANFIS classifier, which was trained using the combined data groups to identify all the work rate categories. The fuzzy rule architecture of the ANFIS models was based on a Gaussian curve membership function, as follows:

$$G(x) = exp\left[\frac{-(x-\mu)^2}{2\sigma^2}\right] \tag{6.1}$$

where μ and σ are the parameters of the membership function governing the Gaussian curve function associated with each input variable (i.e., $\%HR_{max}$, HR_{rest}, and body weight). All ANFIS models were developed using the fuzzy logic toolbox in MATLAB (version 7.5.0).

The training dataset was separated into four groups according to work rate category (198 data samples in the VL category, 178 in L, 85 in M, and 35 in H), each of which was used to develop a corresponding ANFIS model. Table 6.3 presents a description of the four ANFIS models. These models were then combined to form the ANFIS classifier, with eight fuzzy rules, eight membership functions assigned to each input variable, and a total of 80 modifiable parameters (48 premise parameters and 32 consequent parameters) (Appendix K). The ANFIS classifier was trained using the combined data group samples (496 samples) for 1000 training epochs.

Table 6.3: Description of the four ANFIS models associated with the four work rate

Model	**Associated category**	**Clustering parameters**	**No. of clusters (IF-THEN rules)**	**No. of mf**	**No. of modifiable parameters**	
					Premise	**Consequent**
ANFIS model 1	VL	$r = 0.5$, $\eta = 1.5$, $\bar{\in} = 0.9$, and $\underline{\in} = 0.7$	2	2	12	8
ANFIS model 2	L	$r = 0.9$, $\eta = 1.5$, $\bar{\in} = 0.9$, and $\underline{\in} = 0.9$	1	1	6	4
ANFIS model 3	M	$r = 0.9$, $\eta = 1.5$, $\bar{\in} = 0.9$, and $\underline{\in} = 0.9$	1	1	6	4
ANFIS model 4	H	$r = 0.9$, $\eta = 1.1$, $\bar{\in} = 0.3$, and $\underline{\in} = 0.3$	4	4	24	16

Note. VL: very light rate; L: light rate; M: moderate rate; H: heavy rate; Premise: IF part of a fuzzy rule; Consequent: THEN part of a fuzzy rule; r: cluster radius; η: squash factor (penalty radius/cluster radius); $\bar{\in}$: accept ratio; $\underline{\in}$: reject ratio; mf: membership function associated with each input variable.

To determine the significance of the selected input variables (%HR_{max}, HR_{rest}, and body weight) for classifying work rate, changes in the shape of the Gaussian membership function of the input variables before and after training were plotted. Changes in the membership function of inputs after training indicate the impact of inputs on output detection (Yildiz et al., 2009). Results indicated considerable changes in membership function associated with %HR_{max} and HR_{rest} before and after training. However, membership function changes associated with body weight were less significant. Therefore, it can be concluded that %HR_{max} and HR_{rest} have greater impact than body weight on work rate classification. Figures 6-2 and 6-3 show the initial and final membership function associated with %HR_{max} and HR_{rest}, respectively.

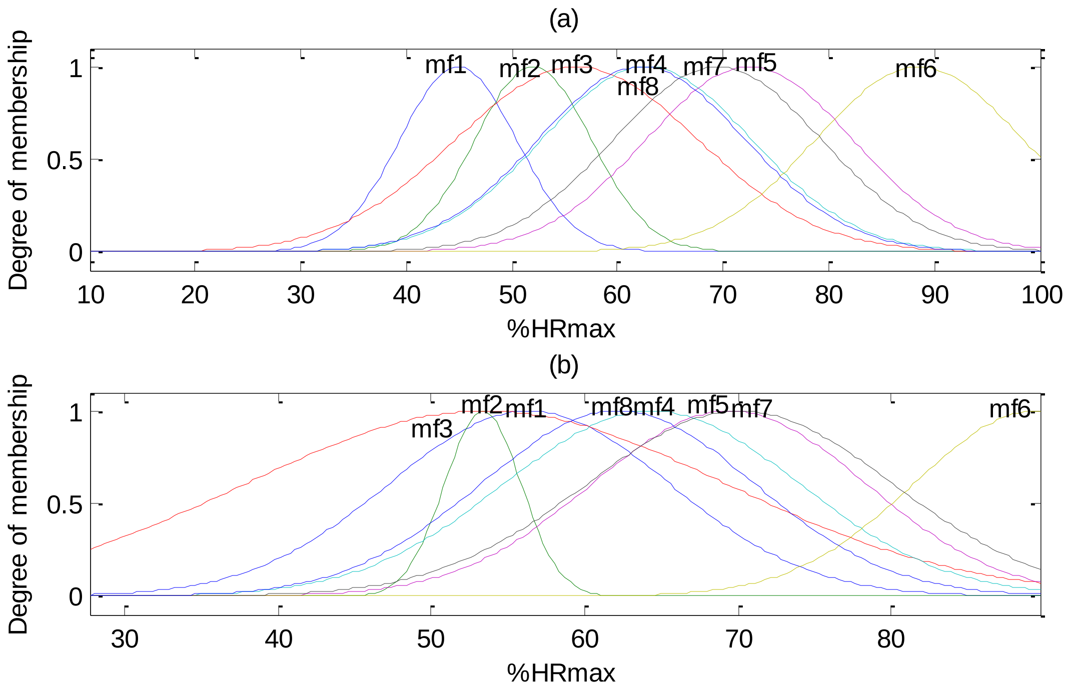

Figure 6-2: (a) Initial and (b) final Gaussian membership functions associated with $\%HR_{max}$

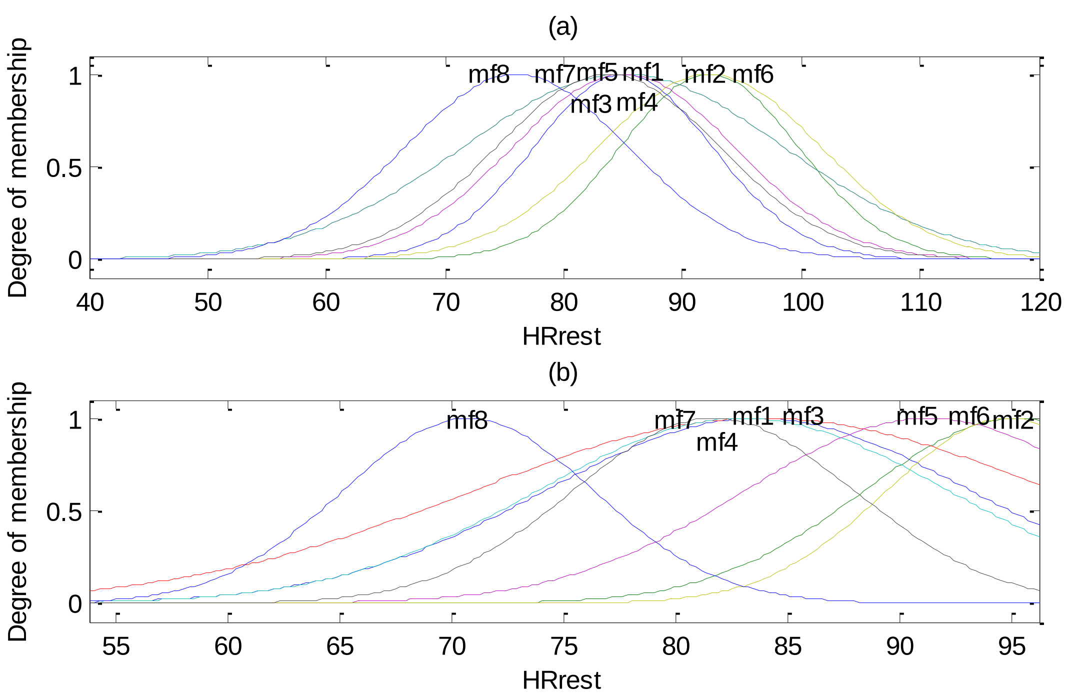

Figure 6-3: (a) Initial and (b) final Gaussian membership functions associated with HR_{rest}

6.3.3.3 Classifier testing and comparison

The overall and relative (i.e., separately in each stage) performance of the developed ANFIS classifier was assessed using the test dataset for the remaining eight participants that had not been used to develop the classifier. The test dataset comprised 106 data samples in the VL category, 99 in the L category, 37 in the M category, and eight in the H category. Of these eight participants, three were unfit and four were older. In addition, the classifier's performance was compared with the current practice (i.e., based on %HRR) for estimating work rate, as recommended in many studies (Haskell and Pollock, 1996; Pollock et al., 1998; ACSM, 2006). This method uses %HRR $((HR\text{-}HR_{rest})/(HR_{max}\text{-}HR_{rest})\times 100)$ to classify physical activities lasting up to 60 minutes according to the following predetermined limits: If %HRR<24 then work rate is VL, if 25<%HRR<44 then work rate is L, if 45<%HRR<59 then work rate is M, and if 60<%HRR<84 then work rate is H.

6.3.4 Statistical analysis

Student's two-tailed t-test for independent samples was used to determine the impact of age on relative workload (%VO_{2max}) associated with the different steps of the step-test using measured VO_2 and VO_{2max} on all 28 participants. A threshold of $p<0.05$ was considered statistically significant. A confusion matrix was used to assess the classification accuracy of the classifier. This matrix contains information about desired and actual (predicted) classifications, allowing detection of confused categories. Desired classifications were assigned to rows and actual outputs to columns. Performance in identifying each work rate category was assessed using three statistical parameters: sensitivity, specificity, and accuracy (Yildiz et al., 2009; Leondes, 2007), generally defined as follows:

$$Accuracy = \frac{Number\ of\ correct\ classifications}{Total\ number\ of\ cases} \quad (6.2)$$

$$Sensitivity = \frac{Number\ of\ true\ positive\ classifications}{Total\ number\ of\ positive\ cases} \quad (6.3)$$

$$Specificity = \frac{Number\ of\ true\ negative\ classifications}{Total\ number\ of\ negative\ cases} \quad (6.4)$$

6.4 Results

6.4.1 Selecting significant input variables

Table 6.4 presents the work rate category distribution associated with each step (exertion level) of the step-test. On average, step 0 represents very light rate, steps 1 and 2 light rate, step 3 moderate rate, and step 4 heavy rate. Results indicate that the step-test can yield exertion levels ranging from very light to heavy, and that intersubject variability has an impact on work rate classification. For example, all participants experienced a light work rate in step 1, compared with 73% of participants who experienced light work rate and 27% moderate work rate in step 2. The two-tailed independent samples t-test showed no significant differences in $\%VO_{2max}$ between older and young participants (Table 6.5), indicating a negligible impact of age on work rate assessment and classification.

Table 6.4: Work rates and categories associated with the different steps of the step-test

Step	$\bar{x}$ (*SD*)	Work rate category (Prevalent)	Classification			
			VL	L	M	H
0	11.41 (1.91)	Very light	100%	-	-	-
1	28.49 (4.29)	Light	-	100%	-	-
2	38.04 (6.64)	Light	-	73%	27%	-
3	48.26 (8.02)	Moderate	-	28%	61%	11%
4	59.82 (9.25)	High	-	-	33%	67%

Note. $\bar{x}$: average $\%VO_{2max}$ (%); *SD*: standard deviation of $\%VO_{2max}$; VL: very light rate; L: light rate; M: moderate rate; H: heavy rate.

Table 6.5: Mean $\%VO_{2max}$ between older and young participants during the steps of the step-test

Step	**Older participants (n=14)**		**Young participants (n=14)**		**Difference**		
	$\bar{x}$	***SD***	$\bar{x}$	***SD***	**AVR**	**p-value**	**Statistical significance**
0	11.10	1.71	11.81	2.18	-0.71	0.46	NS
1	29.57	4.80	27.14	3.36	2.43	0.23	NS
2	39.44	6.99	36.29	6.18	3.15	0.33	NS
3	50.35	9.10	45.65	5.96	4.7	0.21	NS
4	62.54	10.14	56.42	7.20	6.12	0.15	NS

Note. $\bar{x}$: average $\%VO_{2max}$ (%); *SD*: standard deviation of $\%VO_{2max}$ values; AVR: average difference between groups' $\%VO_{2max}$ (%); NS: non-significant difference ($p > 0.05$).

Table 6.6 presents the overall and relative classification accuracy of the most significant classifiers developed using different combinations of potential input variables for backward selection. Results show an average overall work rate classification accuracy of 78.25% using only the HR monitoring variables (HR, HR_{max}, and HR_{rest}). Overall accuracy improved by 7% when breath rate was included. In addition, greater overall classification accuracy was obtained when physical fitness indicators were included than when BR was included (8% with BMI and 12.5% with body weight). Of the developed classifiers, the classifier including body weight and HR monitoring variables yielded the highest overall classification accuracy (Table 6.6), with higher accuracy than the other classifiers for VL, M, and H work rates, but average accuracy for light work rate (85%). Therefore, $\%HR_{max}$, HR_{rest}, and body weight were selected as the significant physiological variables.

Table 6.6: Average classification accuracy associated with different classifiers

Sets of input variables	Accuracy (%)				
	Overall	VL	L	M	H
{$\%HR_{max}$, HR_{rest}}	78.25	86	81	55	94
{$\%HR_{max}$, HR_{rest}, BR}	85.25	90	83	71	100
{$\%HR_{max}$, HR_{rest}, BMI}	86.5	93	89	67	100
{$\%HR_{max}$, HR_{rest}, body weight}	91	96	85	87	100
{$\%HR_{max}$, HR_{rest}, body weight, BR}	86.75	94	90	65	100
Average	85.55	91.8	85.6	69	98.8

Note. $\%HR_{max}$: percentage of maximal heart rate; HR_{rest}: heart rate at rest (bpm); BR: breath rate (breaths/min); BMI: body mass index ($kg.m^{-2}$); VL: very light rate; L: light rate; M: moderate rate; H: heavy rate.

6.4.2 Testing the developed ANFIS classifier

The classification results associated with the two methods (ANFIS classifier and %HRR method) are presented as confusion matrices in Table 6.7(a). Results for the ANFIS classifier show decreasing classification error with increasing work rate (from light to heavy). For example, 19.19% of the light work categories were wrongly classified as very light (17.17%) and moderate (2.02%). The percent misclassified was lower for moderate (13.5% misclassified as light) and heavy (0% misclassified) categories. In contrast, results for the %HRR classification method show increasing classification error with increasing work rate. For example, the percent misclassified in the light, moderate, and heavy work categories was 56.57%, 73%, and 100%, respectively. On the other hand, results show that %HRR classification yielded fewer misclassifications than the ANFIS classifier for very light work rate.

Table 6.7(b) compares the classification performance of the two methods in terms of sensitivity, specificity, and accuracy. Results indicate that the ANFIS classifier provides superior overall accuracy at 93% (sensitivity, 90.7%; specificity, 95.2%) compared to 63.4% (sensitivity, 42.3%; specificity, 84.5%) for %HRR, and that the relative classification performance of the ANFIS classifier was also superior for the different rates. The highest relative classification accuracy for the ANFIS classifier was obtained with heavy work rates (100%) and the lowest for light work rates (87.1%). In contrast, the highest relative classification accuracy for %HRR was obtained for very light work rates (78.5%) and the lowest for heavy work rates (49.8%).

Table 6.7: Comparisons between ANFIS and %HRR classification methods

(a) Confusion matrix associated with ANFIS / %HRR classification.

Predicted	Desired (True rate)			
	VL	L	M	H
VL	101/105	17/56	0/4	0/0
L	5/1	80/43	5/22	0/3
M	0/0	2/0	32/10	0/5
H	0/0	0/0	0/1	8/0

Note. Predicted: predicted work rate category according to ANFIS and %HRR classification; Desired: actual work rate category according to measured $\%VO_{2max}$; VL: very light rate; L: light rate; M: moderate rate; H: heavy rate.

(b) Classification performance in terms of sensitivity, specificity, and accuracy.

Work rate	ANFIS classifier			% HRR classification method		
	Sensitivity (%)	Specificity (%)	Accuracy (%)	Sensitivity (%)	Specificity (%)	Accuracy (%)
VL	95.3	88.2	91.8	99	58	78.5
L	80.8	93.4	87.1	43	82.8	62.9
M	86.5	99.1	92.8	27	97.7	62.4
H	100	100	100	0	99.6	49.8
Average	90.7	95.2	93	42.3	84.5	63.4

Note. VL: very light rate; L: light rate; M: moderate rate; H: heavy rate.

6.5 Discussion

The analysis of the step-test data indicated that the test involves different work rates ranging from very light to heavy, according to the U.S. department of Health and Human

Services (1996). However, the determination of the work rate was considerably affected by intersubject variability, indicated by the high classification variability associated with steps 2, 3, and 4 (Table 6.4). The results show that age has no significant impact on work rate assessment under different workloads. This finding is supported by Hellerstein (1973) and Franklin et al. (1980). A possible explanation for this observation is the fact that the majority of the older participants were active, which slows the rate of decline in VO_{2max} (Wilmore and Costill, 2005). Studies have shown that physical activity level (active or inactive) has a greater impact on performance than age (Rikli and Busch, 1986; Trappe et al., 1996; Trappe et al., 1996). A decline in VO_{2max} of approximately 15% per decade was reported for inactive individuals versus 5% per decade for active individuals. The selection of input variables demonstrated the significance of $\%HR_{max}$, HR_{rest}, and body weight in yielding the best classification accuracy. Although age in itself showed no significant impact on $\%VO_{2max}$, $\%HR_{max}$ (which involves age indirectly) had a significant impact on $\%VO_{2max}$. This is due to two factors that limit the relationship between $\%HR_{max}$ and $\%VO_{2max}$: the influence of HR on $\%VO_{2max}$ (which is not influenced by training) and the influence of age on $\%VO_{2max}$ (which is influenced by training) (Ragbag, 2003). Plotting of the membership functions associated with these input variables before and after classifier training revealed the significant role of HR monitoring variables in determining work rate over the fitness level indicator.

The confusion matrix showed that the ANFIS classifier perfectly classified all heavy (H) work rate, slightly overestimated very light (VL) (4.7%) and part of light (L) (2%) work rates, and underestimated moderate (M) (13.5%) and the remaining part of light (17%) work rates. The fact that these misclassifications occurred between two adjacent work rate categories only (i.e., between VL and L or L and M) indicates the superiority of the proposed ANFIS classifier in preventing or significantly reducing the potential for undue fatigue over the usual %HRR classification. The results show that the ANFIS classifier provides higher accuracy (as well as sensitivity and specificity) than %HRR classification, with the highest accuracy difference obtained for H work rates and the lowest accuracy difference for VL work rates. In addition, the ANFIS classifier provides a better balance between sensitivity and specificity for the different rates, such that most work rate categories were classified correctly (90.7% of the time, on average) and only a few were misclassified (4.8% of the time, on average). In particular, this classifier can positively identify all heavy work rates (sensitivity = 100%) with no underestimations (specificity = 100%). This could make a significant contribution to maintaining workers' safety through optimal work design and job assignment, particularly in heavy industries.

In practice, the proposed ANFIS classifier provides a simple and practical method for work rate classification in any work environment. Although adequate knowledge of MATLAB is required to develop the classifier and adapt its rule-base to new data, it can then be implemented in Excel (Appendix L), which researchers and practitioners can easily apply as a decision-making tool. (A complete Excel file implementing the model can be obtained by contacting the first author of the paper). HR can be monitored during different activities in a work day, and a HR value corresponding to a certain task—in addition to the age-based HR_{max}, HR_{rest}, and body weight—can be entered into the classifier rule-base to obtain the corresponding work rate category: VL, L, M, or H. Usually, the HR value deemed representative of a task is the average HR during a time period the task is performed. Determination of task HR therefore requires a work observation study. This simple method has the potential to support a wide range of applications in industry. For instance, workers' safety and accident prevention could be improved by continuously monitoring HR online and feeding the measured inputs into the classifier rule-base, which could then trigger visual and/or audible warning signals for predefined potential risks (e.g., performing heavy activity for long periods or in hot temperatures). However, just as is the case with other models, practitioners should be aware that the classifier developed in this study will overestimate $\%VO_{2max}$ (work rate) when a significant thermal pulse is present. Hence, the HR thermal component (thermal pulse) must be removed at the data preparation stage prior to use (Vogt et al., 1970, 1973). Thanks to recent technological developments, core temperature can now be measured easily and noninvasively during actual work (e.g., using VitalSense), and could be included as an input variable in the classifier. Despite the promising results of this study, however, the ANFIS classifier has not been tested extensively or with actual field data. Further studies could include a larger number and variety of participants and a variety of actual work activities with different rates for classifier training and validation. Moreover, investigating the influence of different membership functions (i.e., triangular) could further improve classifier performance. The purpose of this study was to develop a simple and practical approach to categorizing physiological work demand in order to help prevent excessive physical fatigue that could impact performance and safety. Our results show that intelligent systems can make optimal use of basic data that is easily measured in the field and does not require sophisticated equipment.

Applying recent mathematical methods and software, the proposed ANFIS classifier improves on the work rate classification methods currently used by practitioners and researchers.

6.6 Conclusion

This paper presents a new and practical approach for classifying work rate into four categories (VL, L, M, and H) based on easily measured variables (%HR_{max}, HR_{rest}, and body weight). Unlike the current classification method, our proposed modeling approach considers individual physical fitness, which plays a significant role in reducing the effect of intersubject variability. The motivation for using fuzzy logic was the presence of uncertainty in work rate classification due to imprecise boundaries between work rate categories and high intersubject variability. The proposed ANFIS classifier demonstrated superior performance in terms of both overall and relative accuracy, sensitivity, and specificity compared to current practice (%HRR classification). Moreover, it strikes a balance between sensitivity and specificity for different work rates (particularly for heavy work rates), which can make a substantial contribution to improve workers' safety and prevent accidents. The proposed classifier represents not only a new application of fuzzy logic for work rate classification, it also provides a practical, easy-to-implement, and noninvasive classification system that combines advanced technology with simple, low-cost HR measurement.

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CHAPTER 7: GENERAL DISCUSSION

7.1 Review of implemented methods

The methods implemented in this research can be grouped into four categories: methods related to data acquisition, methods related to modeling, methods related to data analysis, and methods related to validation.

7.1.1. Methods related to data acquisition

The databases that are used in this dissertation for rule-base generation and model development were collected using six approaches: Meyer and Flenghi step-test, maximal multistage treadmill test, regeneration release work, pre-commercial thinning, short interviews, and questionnaires. Meyer and Flenghi step-test was used to obtain input (HR, HR_{rest}, BR)-output (VO_2) data during different intensity levels as represented by different test stages. These data were used to develop the VO_2 estimation models proposed in Chapters 4 and 5 and the classifier proposed in Chapter 6. In this research, all participants (28 university students and employees, 22 pre-commercial thinners, and 8 regeneration release workers) performed the Meyer and Flenghi step-test primarily because it is simple, cost-effective, practical, and can be implemented safely without imposing high cardiac strain. An additional advantage is that step frequency is sufficiently low for any worker to be able to keep pace at all four step heights, to offer superior overall test precision and robustness. The simplicity and practicality of this step-test allowed us to conduct the test both in laboratory as well as in field near the treated patch. This step-test was validated against other graded submaximal exertion tests (Meyer and Flenghi, 1995) and against a maximal treadmill test (Imbeau et al., 2009). In fact, Imbeau et al. (2010) demonstrated that the highest exertion level on this test reached by a group of forest workers corresponded well to the exertion generally measured during typical regeneration release work. A more closely detailed description of the Meyer and Flenghi step-test is provided in Chapter 4.

The participants in our study (28 university students and employees) also performed a maximal multistage treadmill test in laboratory to determine maximal cardiorespiratory fitness (VO_{2max}). The test began with a warm up period for five minutes at a constant speed and slope of 7 $km.h^{-1}$ and 3%, respectively. After five minutes, the speed was increased to 12 $km.h^{-1}$ and was then increased by 1 $km.h^{-1}$ every two minutes until exhaustion, while the slope remained constant throughout the test. The measured VO_{2max} values were used as target output to train the ANFIS classifier to categorize work rate into four categories more closely examined in Chapter 6.

Field experiments were conducted in softwood plantations or naturally regenerated stands in various areas throughout the Province of Quebec to ensure data representativeness and model generalizability. Thirty forest workers participated in the field experiments in which eight performed regeneration release treatment (Chapters 4 and 5) and 22 performed pre-commercial thinning (Chapters 5). The regeneration release mainly involved cutting competing trees in the forest using a motor-manual brush saw after the forest harvest in order to improve forest growth. During this process, rest periods and other related activities (e.g., refuelling, filling the brush saw blade, and movement within the field) were also observed to ensure variability of data.

The pre-commercial thinning cuts down undesirable trees from the forest using a motor-manual brush saw with the intent to produce healthier, better quality, and faster growing trees. In general, the pre-commercial thinning involves similar work activities to those involved in regeneration release. However, the physiological demands of both treatments were different due to the differences in density, height, and diameter of trees to be cut in both treatments (the regeneration release treatment is conducted in younger forests while the pre-commercial thinning is conducted in older forests). Data collected from field experiments described actual work activities with different intensities and therefore using this data in model development and validation added more creditability to the research. All participants took part in short interviews and surveys to determine their eligibility and record their physical characteristics such as age, weight and height, which were then used in models development and validation.

During all experiments, heart rate was continuously measured using a Polar Electro HR monitor (S-210) and a chest strap (T-61 coded). This HR monitoring system was ideal for use in our research since it is light, comfortable, and has an easy-to-use interface and easy-to-read display. This made it practical for the prolonged field measurements inherent to our study and it was user-friendly for older participants who were not familiar with the Polar technology. Also, it being water-resistant made the monitor invaluable for use in field measurements during rainy days. Oxygen consumption measurements during the step-test and field work activities were monitored using a portable oximeter (Cosmed Fitmate PRO). This instrument was appropriate for our research especially for filed experiments because it is considered one of the smallest and lightest portable laboratories for fitness assessment and functional evaluation. It is equipped with a fast built-in printer, which was useful for onsite data collection and assessment. Also, its easy-to-use software made it possible to download all the data to a computer for permanent storage and analysis.

Since the silvicultural activities were conducted in hot weather conditions, the HR data collected during work contained a thermal pulse, which is an increase in HR due to an increase in body core temperature. Therefore, the HR data had to be adjusted to the thermal pulse before it could be used in model development and validation using the method proposed by Vogt et al. (1970) to avoid a significant VO_2 overestimation. Vogt and colleagues suggested the use of the HR value measured in the fourth minute after the beginning of a rest period (HR^{4th}) to estimate the elevation in HR. They used a linear interpolation between two consecutive HR^{4th} measurements (belonging to two consecutive rest periods) to graphically determine the thermal pulses during the entire work-rest cycle. More details can be found in Vogt et al. (1970).

7.1.2. Methods related to modeling

Estimating oxygen consumption or classifying work rate using heart rate measurements is often accompanied by some degree of uncertainty, inaccuracy and nonlinearity. Although classical methods (e.g., regression analysis) have been used extensively, they lack the ability to account for the uncertainties inherent to the human physiological system, expert knowledge resembling, and nonlinear input-output mapping. ANFIS, on the other hand, has proven to be an efficient means of tackling real-life problems that involve uncertainty, vagueness and nonlinearity. For this reason, ANFIS has been used in various fields especially in medical and biomedical applications (Yildiz et al., 2009). However, its use in the human work physiology field is very limited. Therefore, in this dissertation, ANFIS was the main mathematical method used to develop practical models to estimate VO_2 (Chapters 4 and 5) and to classify work rate (Chapter 6). The fuzzy logic toolbox in MATLAB version 7.5.0 was used to develop these models. A critical review of soft computing techniques and particularly ANFIS is found in Chapter 3.

The rule bases for all developed models were established objectively (based on input-output data) using the subtractive clustering algorithm. The use of this particular algorithm in this dissertation is due to its capability and efficiency in automatic rule generation. It assumes that each data point is a potential cluster center and calculates a measure of the likelihood that each data point would define the cluster center, based on the potential of surrounding data points. By using this method, the quantity of calculation is in proportion to the number of data points rather than dimensions. The initial parameters of the membership functions were determined based on the selected subtractive clustering parameters (i.e., cluster radius (r), squash factor (η), accept ratio ($\bar{\epsilon}$), and reject ratio ($\underline{\epsilon}$)), which were optimally determined by an enumerative search method. The processing time of clustering and extracting fuzzy rules was different from model to model. For example, the processing time for the enumerative search process ranged from 14 to 19 seconds (for individual models) and approximately 2.5 minutes (for the general ANFIS model) using a MATLAB code on an AMD Athlon 1.20 GHz computer. After determining the optimal clustering parameters, an initial fuzzy inference system was developed in less than 2 seconds (for individual and general models) using the Fuzzy Logic Toolbox (MATLAB 7.5.0). The processing time for optimizing the initial parameters of the membership functions (using the back-propagation gradient descent method in combination with the least squares method) was approximately 3 minutes (for individual models) and 8 seconds (for the general ANFIS model) on the same processor. More details about subtractive clustering algorithm are found in Chapter 3.

The backward selection method used in Chapters 5 and 6 was applied in to determine significant inputs to the proposed models. This method begins with a full set of inputs in the model wherein the least significant input (e.g., yields smallest RMSE) is then removed and the model is retrained using the training dataset. This process continues until the estimation error reaches a predetermined limit or there are no more inputs to remove. The main advantage of the backward selection method is that it allows the examination of the effect of all combined inputs in the proposed models before the insignificant inputs are eliminated. In some cases, it is possible that the joint estimation capability of all inputs combined is high even though the estimation capability of any of their subsets is not high. With other selection methods (e.g., forward selection and stepwise regression), there is the chance that the joint estimation capability of all inputs (if any input or subset of all inputs have low estimation capability) cannot be seen. A detailed description of the backward selection method is provided in Appendix J.

7.1.3. Methods related to validation

The holdout method, also known as the split sample method, was used to validate the General ANFIS model (Chapter 4) and the ANFIS classifier (Chapter 6). The application of this method is simple since it involves a random partition of the data into two sets (a training set and a test set) based on a predetermined percentage (e.g., 70%/30%) (Molinaro et al., 2005). In addition, the 10-fold cross validation method was simultaneously used with the backward selection for accurate performance assessment of the ANFIS prediction model (Chapter 5). This method has been found superior to other validation methods (e.g., holdout, bootstrap and leave-one-out cross validation methods) in determining the generalization error in model selection problems (Breiman and Spector, 1992; Kohavi, 1995; Molinaro et al., 2005). This method involves the random partition of data into 10 partitions of equal size (n/10). Nine partitions are assigned to the training set, while the remaining one is assigned to the test set. This process is repeated 10 times so that each time results in different training and test sets. Afterwards, the average performance of the 10 times is calculated. A detailed description of the implementation of the 10-fold cross validation is provided in Appendix F.

7.1.4. Methods related to analysis

Data analysis related to the developed models in Chapter 4 (individualized models and General ANFIS model) and Chapter 5 (ANFIS prediction model) was performed throughout the HR range as well as for three HR categories: very light work: <80 bpm; light work: 80-100 bpm; and moderate to heavy work: >100bpm. Data analysis related to the developed ANFIS classifier (Chapter 6) was performed for four work rate categories: very light ($\%VO_{2max}<24$), light ($25<\%VO_{2max}<44$), moderate ($45<\%VO_{2max}<59$), and heavy ($60<\%VO_{2max}<84$).

In Chapter 4, the assessment of the performance of the individualized models and the General ANFIS model in estimating VO_2 was based on: estimation errors (RMSE, MAPE, and MAE), Student's two-tailed t-test for paired observations ($p < 0.05$), Bland-Altman plot and limits of agreement (LOA), and coefficient of variation (CV). The performance of the developed models were compared with that of traditional models (linear calibration and Flex-HR methods), as well as with measured VO_2 values. In Chapter 5, the assessment of the performance of the ANFIS prediction model in VO_2 estimation was based on: estimation errors (MAR and MAPE), Student's two-tailed t-test for paired observations ($p < 0.05$), Bland-Altman plot and limits of agreement (LOA), and coefficient of variation (CV). The VO_2 estimates from the ANFIS prediction model were compared with measured VO_2 values, as well as with the estimates from Rennie et al.'s and Keytel et al.'s models. In Chapter 6, Student's two-tailed t-test for independent samples ($p < 0.05$) was used to determine the impact of age on relative workload

($\%VO_{2max}$) associated with the different steps of the step-test. The performance of the ANFIS classifier in classifying work rate was assessed using a confusion matrix analysis and statistical parameters (accuracy, sensitivity, and specificity). Additionally, the classifier's performance was compared with the current practice (i.e., based on %HRR) for estimating work rate.

7.2 Summary and main results

This research was motivated by the fact that many existing industries still require physically demanding labor, which is the main cause of undue fatigue, reduced productivity, and poor quality. Understanding physiological demands will help practitioners and researchers to effectively design work methods, workplaces, and work-rest cycles, which play an important role in ensuring workers' safety and productivity as well as operational efficiency. Not only measuring but also assessing physiological demands of physical activities achieves an adequate level of understanding these demands. Therefore, the main objective of this research was to develop simple and practical yet accurate means to help understand the physiological demands placed on workers by different physical work activities. In the light of this objective, two directions were explored in this research: measuring and assessing the physiological demands of physically demanding jobs. The first direction was concerned with developing practical models to estimate the absolute amount of energy (i.e., VO_2) expended by workers during work activities (Chapters 4 and 5). The second direction was concerned with developing a practical model to classify work rate based on estimates of relative energy (i.e., % VO_{2max}) expended during work activities (Chapter 6).

The linear calibration method is one of the most widely used methods for VO_2 estimation. However, this method is limited by two major drawbacks that impede its accuracy and use in field research. First, it is costly and time consuming to establish individual calibration curves at workplaces with large populations. Second, because the relationship between HR and VO_2 at low work intensity is nonlinear and often deviates from the calibration curve, the linear calibration method cannot accurately determine energy expenditure. From this perspective, Chapter 4 was dedicated to improving current methods that require individual calibration (i.e., linear calibration and Flex-HR methods) at both individual and group levels. Firstly, we sought to improve the accuracy of current methods by managing the nonlinearity between HR and VO_2 especially at low work intensities. Two approaches were used to achieve this goal. In the first approach, individuals performed the Meyer and Flenghi step-test where HR and VO_2 were measured throughout different step-test stages. The VO_2-HR relationship was described using ANFIS, which has proven efficiency in approximating nonlinear functions. However, in the second approach, the analytical analysis of individuals' VO_2-HR data indicated a bilinear relationship (bilinear frontier), which was described using a unit step function, eq. (4.3). Results from laboratory and field studies indicated that the individual ANFIS model outperformed current methods throughout the HR range (laboratory RMSE= 1 ml/kg.min; field RMSE= 2.8 ml/kg.min) and at low work intensities (RMSE= 0.1 ml/kg.min for laboratory and field). A significant reduction in VO_2 estimation error was reported when individual ANFIS was used in place of current methods. For instance, individual ANFIS yielded an approximate 39% (laboratory study) and 23% (field study) in overall reduction in RMSE when it was used instead of linear calibration method (Table 4.4). However, a reduction in RMSE of approximately 80% (according to laboratory study) and 95% (according to field study) was reported at low work intensities (Table 4.2). Results from the field study demonstrated the outperformance of the proposed analytical model (RMSE= 3.2 ml/kg.min) over current methods. This indicated a reduction in the overall RMSE of approximately 12% when the analytical model was used instead of both linear calibration and Flex-HR methods. Approximately, 76% and 50% of this reduction was accounted for the improvement in VO_2 estimation at low work intensities for the linear calibration and Flex-HR methods, respectively. Based on these results, the proposed individual ANFIS and analytical models are recommended for use in work environments with smaller populations or when accurate VO_2 estimation (at the individual level) is desired.

Secondly, we aimed to improve the practicality and usability of current VO_2 estimation methods especially for use in larger work populations, where it is costly and time consuming for individuals to perform calibration tests. Therefore, a general model was developed using neuro-fuzzy systems to estimate VO_2 from HR monitoring without the need for individual calibration tests. The General ANFIS performed comparably or slightly better on the overall HR range (MAE=4.4 ml/kg.min) and for the lower HR range (MAE=1.3 ml/kg.min) when compared to the linear calibration and Flex-HR models. However, it produced the largest estimation errors in the medium and higher HR ranges (MAE=3.3 ml/kg.min). The analysis based on paired t-test and the LOA indicated that the VO_2 values estimated by the General ANFIS model were not significantly different from the measured values. This strongly implies that the General ANFIS model can replace the individual linear calibration and the Flex-HR models for VO_2 estimation especially in large population work environments in which it is more desirable to avoid subjecting each individual to a graded exercise test and still obtain an accurate estimation of VO_2.

Chapter 5 presented a new approach for VO_2 estimation without the need for individual calibration using ANFIS. The proposed approach was motivated by the Flex-HR method, which is considered one of the accurate methods for VO_2 estimation. The idea was to estimate the Flex-HR parameters using easily measured variables without having to collect individual calibration data. The ANFIS prediction model developed in this chapter is composed of three ANFIS modules for estimating the Flex-HR parameters, namely ANFIS module 1 (associated with VO_2 rest), ANFIS module 2 (associated with the Flex point), and ANFIS module 3 (associated with the slope and intercept of the linear VO_2-HR curve). The development of each module involved three steps: input screening, model selection, and final model building. The backward selection method was put in a 10-fold cross validation framework for simultaneous input screening and model selection. Results indicated that ANFIS module 1 was impacted by (age, weight, height, and HR_{rest}), ANFIS module 2 by (weight, BMI, and HR_{rest}), and ANFIS module 3 by (age, weight, height, BMI, and HR_{rest}). Results showed that there was no significant difference between the observed parameters and the ones estimated using the ANFIS modules. Furthermore, the analysis based on paired t-test and LOA indicated no significant difference between the measured VO_2 values and the ones estimated by the ANFIS prediction model. The proposed ANFIS prediction model (MAE=3 ml/kg.min) showed better performance than the other general models (MAE=7 and 6 ml/kg.min for Rennie et al.'s and Keytel et al.'s models, respectively) and comparable performance with the standard Flex-HR method (MAE=2.3 ml/kg.min), throughout the HR range. This strongly suggests that the proposed ANFIS prediction model is an adequate replacement for the standard Flex-HR method for VO_2 estimation, especially in large population work environments in which it is preferable to avoid having each subject take a graded exercise test to obtain an accurate estimation of VO_2. The proposed model can be implemented as easily as the standard Flex-HR method due to significant advances in the analytical software's development.

Chapter 6 presented a new approach for assessing physical demands of work activities by classifying work rate into four classes (VL, L, M, and H) based on HR monitoring. The proposed ANFIS classifier accounted for intersubject variability by incorporating indicators of physical fitness (i.e., HR_{rest}, bodyweight, and BMI). In this chapter, a three-step approach was used to develop the classifier. First, significant input variables were selected using the entire dataset (from 28 participants). Next, an ANFIS classifier was developed (with the selected input variables) using a training dataset of 20 randomly selected participants. This step involved developing four ANFIS models in which each was trained to classify one of the activity levels (VL, L, M, and H). The four ANFIS models were combined to form the ANFIS classifier that identifies all work rate classes using 8 fuzzy rules. Finally, the ANFIS classifier was tested using a test dataset from the remaining eight participants. Analysis showed that the HR monitoring variables (i.e., $\%HR_{max}$ and HR_{rest}) were the most significant variables followed by the physical fitness indicator (i.e., bodyweight). Results indicated the superiority of the ANFIS classifier with overall accuracy of 93% (sensitivity, 90.7%; specificity, 95.2%) over the current method (%HRR classification method) with overall accuracy of 63.4% (sensitivity, 42.3%; specificity, 84.5%). In addition, the relative classification performance of the ANFIS classifier was better than that of the %HRR classification method during the four intensity levels. The proposed ANFIS classifier represents a practical means to determine from the low cost measurement of HR, a reliable and non-invasive estimate of work intensity experienced by individuals.

7.3 Research contribution

This research significantly contributes to the knowledge and innovation needs of physically demanding industry. Primarily, it presents two individual models (individual ANFIS and analytical models) for VO_2 estimation based on HR measurements. These two models have shown low estimation errors (in comparison to current practices) and have successfully tackled the nonlinearity limitation between VO_2 and HR during low workload activities. Therefore, these two models can be implemented easily in small population work environments and in situations where accurate estimates of EE are required regardless of time and cost in order to achieve effective work design, work-rest patterns and worker selection.

Secondly, this research presented two practical means for EE estimation without the need for any individual calibration or any kind of graded exercise. The first approach provides a general ANFIS model for VO_2 estimation without the need for individual calibration mainly by monitoring HR. This model can be implemented to determine the physiological demands (i.e., EE) of work activities in large population work environments where cost and time are constraints. This will allow for the appropriate work design, the ability to redesign the physically demanding work activities to fit the capabilities of the workforce, to select a specific worker for a certain job, and to design training programs that bring the workforce to expected performance levels. The second approach provides a general model (ANFIS prediction model) to predict individuals' VO_2-HR relationships and ultimately to estimate EE during different work activities using easily measured variables. Unlike the previous general model, the ANFIS prediction model treats different portions of the VO_2-HR relationship by developing three ANFIS modules and therefore providing more information about each individual. For instance, ANFIS module 1 provides an accurate estimate of the resting oxygen consumption, which indicates the daily sedentary energy expenditure. Therefore, ANFIS module 1 has the potential to be implemented in a wide range of applications, such as in sport and health centers to establish dietary intake and weight loss programs, as well as in medical centers and hospitals to determine the caloric demands of patients and thus assess their nutritive needs. On the other hand, determining the Flex point by using ANFIS module 2 helps to distinguish between energy expenditure during rest and during activity. This may find a wide range of applications especially in physically demanding industry since determining worker's Flex point allows one to monitor their work-rest schedules. In general, the ANFIS prediction model provides an individual calibration curve before starting actual work. This will help to determine an individual's physiological/physical characteristics in advance to result in a more suitable work design.

Thirdly, this research presents a practical approach for evaluating the physiological demands of work by classifying work rate. Just by monitoring HR during different work activities, one can apply the HR value corresponding to a certain activity, in addition to the age-based HR_{max}, HR_{rest} and bodyweight, to the rule-base of the ANFIS-based classifier and obtain the intensity level of that activity expressed as one of the following: VL, L, M or H. Assessing the strain from physical work experienced by an individual in many work settings is essential in controlling physical fatigue and therefore improves workers' safety and productivity.

The proposed models represent a new application of the neuro-fuzzy systems for EE estimation and work rate classification. These models can be easily implemented due to recent significant advances in analytical software development. Three articles were produced from this research and submitted to the Applied Ergonomics. In addition to the research supervisor (Dr. Daniel Imbeau) and me, three co-authors contributed to this research, namely Philippe-Antoine Dubé and Denise Dubeau (in the process of data collection of the three articles) and Dr. Richard Labib (in development of the individual analytical model in article 1).

7.4 Research requirements and difficulties

The present research involved two types of experiments – one conducted in the laboratory and the other conducted in the field. Laboratory data collection was based on two types of tests (i.e., Meyer and Flenghi step-test (1995) and a maximal multistage treadmill test), which were carried out by Philippe-Antoine Dubé and Olivier Waddell (Imbeau et al., 2009). Field data collection was based on field step-test and regeneration release work activities. The datasets used in Articles 1 and 2 were obtained from both the laboratory (step-test) and field (field step-test and regeneration release work) experiments. For Article 3, the dataset was obtained from laboratory experiments (step-test and maximal treadmill test). Difficulties associated with the laboratory experiment included a lack of participants (students and employees) who were willing to participate in laboratory experiments either because individuals were unavailable during the summer holiday session or due to the nominal monetary incentive given that the participation period was short.

The main difficulties we experienced in this research, however, revolved around the field data collection. The process of field data collection was divided into four phases each of which was conducted in cooperation with a specific forestry enterprise. Accordingly, forestry workers from four different enterprises in the Province of Quebec participated in this research. Figure 7-1 shows the locations of different forests in which field data collection was performed. Phase 1 took place from July 18 to 22, 2011 to collect field measurements concerning enterprise 1 in Mistassini (location B, approximately 500 km north of Montréal). Phase 2 took place from July 26 to 28, 2011 to collect the field measurements concerning enterprise 2 in the Appalaches Région (location C, approximately 233 km from Montréal). Phase 3 took place from July 30 to August 4, 2011 to collect field measurements concerning enterprise 3 in Mauricie (location D, approximately 122 km from Montréal). Finally, phase 4 took place in Rimouski (location E, approximately 537 km from Montréal) from August 8 to 13, 2011. The research team was required to return to Montréal after each phase in order to rest, analyze the collected data, and prepare the equipment for the subsequent phase. The commute from Montréal to each location required a minimum 2-hour drive off the main road at low speeds to ensure the safety of the team. These commutes took longer when the team was required to derive during the night and meant that the research team was required to travel to the designated location one night before conducting the experiment and stay onsite for the duration of the study because it was necessary to conduct the experiments in the early morning hours. During night, the research team stayed either onsite, in the accommodation provided by the employer, or in a hotel near the site, depending on the distance between the site location and the nearest town.

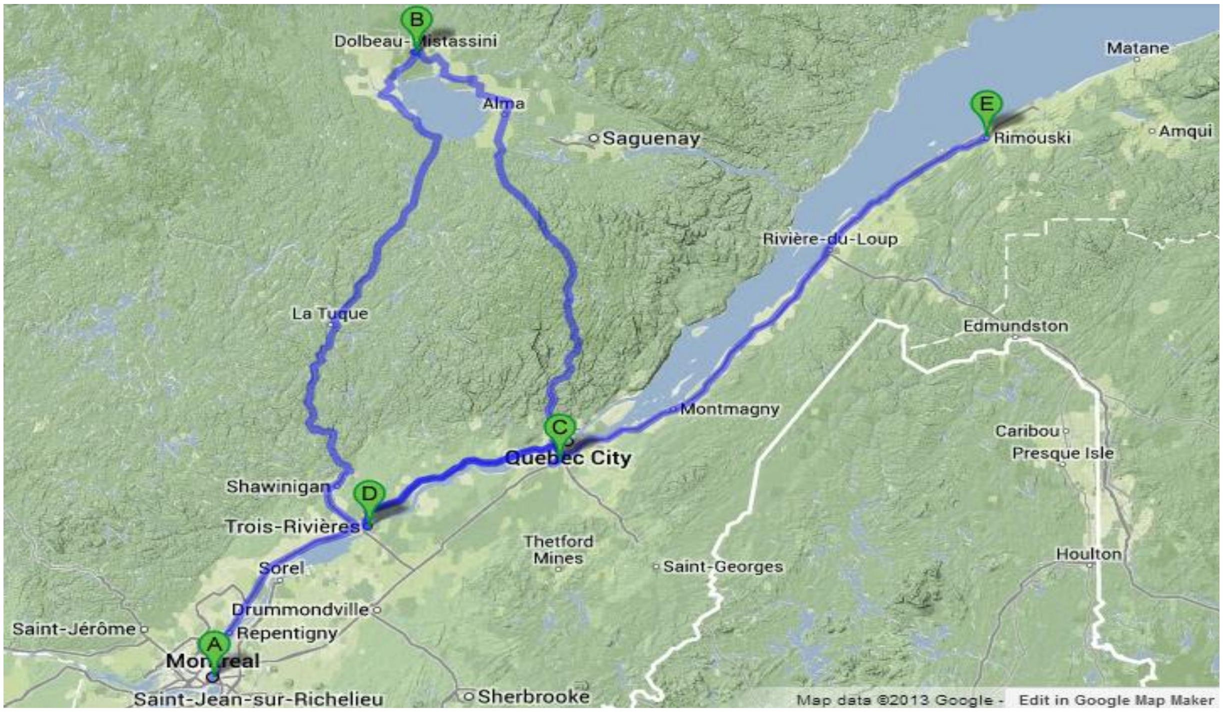

Figure 7-1: Map of different forests considered in this research: (A) Montréal (B) Mistassini (C) Appalaches Région (D) Mauricie (E) Rimouski

Each phase begins with a meeting for the participants wherein the research team explains the terms and conditions of the experiment and the importance of the study. Each experiment was explained in detail to discuss the use of equipment, the “do’s” and “don’ts” of the process (e.g., drinking extra amount of water and avoiding alcohol and smoking), and to obtain the signed consents forms from each worker. Early the following morning prior to breakfast (around 5:00 AM), workers performed a Meyer and Flenghi step-test during which the research team closely observed each one in order to make sure they were keeping the correct pace during the test. After the step-test, the research team fitted each worker with the Polar Electro chest strap to monitor HR during the workday. Then, workers headed to the worksite and prepared their tools (e.g., motor-manual brush saw, blades and fuel) before beginning the day’s work. The research team accompanied the workers during the entire workday in order to prepare for the data collection process, observe the activities, and conduct a time study of each worker. The research team ensured that workers maintained the correct work-rest cycles, did not smoke or drink coffee prior to the test, and stayed calm during the measurement of rest periods. Before midday (between 10:00-11:00 AM), the research team prepared each worker for data collection by fitting each one with the Cosmed Fitmate PRO (in a backpack) and a face mask and ensuring that both were affixed properly. Workers' heart rate and oxygen consumption were measured for an average of 37 minutes during their regular work activities. After the measurement period, the research team removed the Cosmed Fitmate PRO and the face-mask from each worker. While the workers resumed their duties, the research team examined the devices. Since field experiments were scheduled to take place in the early morning, each device required nightly maintenance (e.g., to recharge batteries, to reset Polar Electro and Cosmed Fitmate PRO, and to wash the Polar Electro chest straps and face-masks). The research team was also continuously required to carry the Cosmed Fitmate PRO onsite in order to ensure the accuracy of work-rest cycle measurements. In addition, special care was taken to avoid certain technical complications, which could result from signal loss (due to shifting of the Polar Electro chest strap, especially if it slipped below the chest), a wet Cosmed Fitmate face-mask (due to breathing), and sudden movements of the Cosmed Fitmate cable attached to the chest. One of the Cosmed Fitmate PRO devices was not functioning properly during rain due to the precipitation and wetness of the cable attached to the worker's chest. As a result, the research team was required to continuously dry the cable and attempt to keep the worker out of the rain.

At the end of the workday, all measurements were downloaded to the research team's laptops due to the limited storage capacity of the equipment itself (approximately 72 hours of recording for the Polar Electro) and in order to conduct preliminary analysis of the collected data. Heart rate measurements during silvicultural activities consisted of a thermal component due to working in hot conditions for more than 60 minutes. Therefore, HR measurements were adjusted to take the thermal pulse into consideration before use in this research. Moreover, since data quality was important in model development, the raw data needed to be refined by removing noise and redundancy. For example, although workers were given specific instructions regarding how to perform the step-test, they sometimes found it difficult to remain calm during rest periods and maintain the correct pace during the different steps of the step-test, both of which resulted in unusable data. Other complications included adverse weather conditions such as heat, rain and humidity that affected the productivity of workers and that of the research team. Furthermore, areas of the forest where terrain conditions affected the research team's mobility and ability to observe the workers during work activities, impeded the team's ability to reach treated areas in the forest and thus inhibited data collection in these areas, thereby decreasing the accuracy of the experiment. In addition to the difficulties mentioned above, the research team risked stepping into hidden marshes and risked confrontations with dangerous animals such as bears, bees and snakes in walking the long distances between the road and the treated areas of the forest.

7.5 Future research

The focus of this research was to develop practical approaches for estimating absolute and relative workloads during different work activities. Although the data obtained from forestry work was mainly used to test the developed models, this research provided an assessment of the physiological demands associated with the forestry work activities (i.e., brush cutting and regeneration release work) in Quebec. As expected, additional research is still required to assess the physiological demands of other types of work. Using the developed models to assess the physiological demands of various types of forestry work activities with different workforce demographics (e.g., age, sex, and physical characteristics) will lead to a better understanding of the energy demands required by these activities (Abdelhamid, 1999). This will provide industry managers and decision makers with many opportunities to improve work design and methods and ultimately to improve workers safety and productivity.

Although it has been shown that exercise mode or activity type does not affect the estimation of energy expenditure based on regression analysis, additional research to test the developed fuzzy models based on different types of work activities could offer an interesting component to this research. Another future investigation might involve the use of a larger sample size and variety to train and validate the fuzzy models, which could improve the robustness and the generalizability of the models.

This research focused on assessing the physiological demands of work activities in order to match the demand with an individual's capability to perform the work. However, the individual's capability to perform the work, indicated by VO_{2max}, is difficult to measure in work conditions and could be hazardous depending on the physical fitness level of the individual. To this extent, an interesting future research would be to develop a practical approach to estimate VO_{2max} based on easily measured variables using neuro-fuzzy systems.

Under the field conditions, which involve heavy work intensity and climatic load, heart rate may considerably increase with the increase of body core temperature (Rowell, 1986;

Kampmann et al., 2001). Because this may strongly impact the VO_2-HR relationship, it would be worthwhile to investigate the effect of the raise in HR due to the thermal stress (i.e., thermal pulse) on VO_2 estimation. Future research should also attempt to develop a practical approach based on the fuzzy set theory for VO_2 estimation in high temperature work environments. One way to address this problem would be to incorporate the body core temperature as an input variable to the fuzzy model for the purpose of correcting the established VO_2-HR relationship for the thermal pulses.

Studies have shown that forestry work (e.g., harvesting) may place excessive biomechanical and psychophysical stresses, in addition to the physiological stress, on workers (Scott and Christie, 2004; Christie, 2006). Perhaps a future direction of research would be to measure and evaluate the biomechanical and psychophysical demands placed on the workers during the brush cutting and regeneration release work activities considered in this research. The biomechanical response can be investigated by analysing working postures, while the psychophysical response might be indicated using ratings of perceived exertion (RPE) and body discomfort ratings (Christie, 2006). Investigating both the physical (physiological and biomechanical) and psychophysical demands of work activities will offer a better understanding of the many aspects of fatigue associated with these activities (Abdelhamid, 1999).

Although this research covered a broad age range (from 21 to 64 years, as shown in Chapter 5), it mainly focused on a population of male workers for the following reasons and constraints. Because this particular research requires invasive measurement procedures (e.g., attaching and continuous checking of the Polar Electro chest strap), it was difficult to find willing female participants. Another contributing factor to the gender bias of the study is the relatively small percentage of females involved in physically demanding jobs, particularly in the forestry industry, in which our experiments were conducted. Statistics show that men constitute a majority in most physically demanding industries, such as construction (91% and 88.8% in the US and Canada, respectively), forestry (85.2% in Canada), and mining (86.8% and 81% in the US and Canada, respectively) (Statistics Canada, 2012; Bureau of Labour Statistics, 2013). In spite of this clear male majority, it would be interesting to expand our study to investigate the effect of gender on the developed models and to develop models that would accurately estimate energy expenditure of females at workplaces.

CHAPTER 8: CONCLUSION AND RECOMMENDATIONS

This dissertation presented original approaches for estimating and evaluating energy expenditure in an attempt to better understand the physiological demands of physical work which lead to workers' safety and productivity and operational efficiency. The main objective of this dissertation is to develop simple and practical yet accurate models for estimating absolute and relative workloads (energy expenditure) placed on workers during different physical work activities using heart rate measurements. This research allows decision makers in industry to make job design decisions for maintaining workers' safety, health and productivity. These decisions may include: determining what tasks to be performed, assigning workers to different tasks, determining work-rest cycles, determining the location of work area, scheduling the tasks in the work flow, selecting work methods, and selecting the tool used to do the work. For example, estimating the energy expenditure in various parts of a job helps the decision maker to set the appropriate work-rest cycles. If the energy expenditure during a work activity exceeds 5 cal/min (generally accepted as the maximum sustainable level throughout the workday), then the required rest period should at least equal the work period. Also, if the energy expenditure during an 8-hr workday exceeds 33% of a worker's VO_{2max}, then the decision maker can divide the most demanding jobs into tasks such that each will place less workload on the worker. Other solutions may include: changing work methods, using different tools, assigning more fit workers, or training workers to perform the job efficiently.

Due to uncertainty and nonlinearity in the human physiological system and in order to capture the true relationship between physiological variables, the adaptive neuro-fuzzy inference systems (ANFIS) were applied as the principal mathematical modeling tool. In the first part of the dissertation, we initially proposed individualized models (ANFIS and analytical models) for VO_2 estimation using HR monitoring. Results indicated the better performance of the individual ANFIS (based on laboratory and field data) and analytical (based on field data) models over the traditional VO_2 estimation models (linear calibration and Flex-HR). Results suggested that the proposed individualized models and preferably the individual ANFIS, be used in small population work environments or when very accurate VO_2 estimation is desired. Secondly, we proposed a General ANFIS model that estimates VO_2 without the need for individual calibration.

Results indicated the similarity between the measured VO_2 and estimates from the General ANFIS model. This strongly implies that the General ANFIS model can replace the traditional VO_2 estimation models especially in large population work environments where one cannot afford to have each participant take a graded exercise test and yet obtain a VO_2 estimation that provides reasonable (±10%) accuracy.

In the second part of the dissertation, we proposed a practical approach to estimating energy expenditure based on HR measurements without requiring individual calibration test. The proposed ANFIS prediction model estimates the parameters of the Flex-HR method, which has been recognized as one of the most accurate methods for VO_2 estimation based on HR. Results showed the proposed ANFIS model to be quite accurate (<10%) in estimating measured VO_2, which strongly implies that it can replace the standard Flex-HR method, especially in work environments where one cannot afford to have each participant of a group targeted for study to take a graded exercise test.

In the third part of the dissertation, we proposed a practical approach for classifying work rate into four categories (VL, L, M, and H) based on easily measured variables (%HR_{max}, HR_{rest}, and body weight). The proposed ANFIS classifier considers individual physical fitness, which plays a significant role in reducing the effect of intersubject variability. The proposed ANFIS classifier demonstrated superior performance in terms of both overall and relative accuracy, sensitivity, and specificity when compared to current practice (%HRR classification). Moreover, ANFIS classifier strikes a balance between sensitivity and specificity for different work rates (particularly for heavy work rates), which can make a substantial improvement to workers' safety and help prevent accidents. The proposed classifier provides a practical, easy-to-implement, and noninvasive classification system that combines advanced technology with simple, low-cost HR measurement.

The proposed approaches do not only represent a new application of fuzzy logic for VO_2 estimation and evaluation, but as discussed above, they also provide practical, easy-to-implement, and noninvasive tools that combine advanced technology with simple, low-cost HR measurement. This research opens up a new frontier in the use of soft computing to better understand the physiological impact placed on workers due to physical work.

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APPENDIX A – Developing individual anfis model using matlab

In general, the development of ANFIS models consists of two main steps: developing an initial fuzzy inference system (FIS) and optimizing the developed FIS. The following describes the steps of developing the individual ANFIS model for Subject 3 using MATLAB:

1. Define and save the step-test data associated with Subject 3 in the MATLAB workspace: input (HR) and output (VO_2).
2. Perform an enumerative search for optimal determination of subtractive clustering parameters (i.e., cluster radius (r), squash factor (η), accept ratio ($\bar{\epsilon}$), and reject ratio ($\underline{\epsilon}$)) (Figure A-1). The parameters associated with the model yielding the smallest RMSE are optimal.

```
fid1=fopen('bb.m','w');
load input.mat;
load output.mat;
epoch_n=20;
p=1;
 for squash=0.1:.2:1.5
        for acratio=0.1:.2:1
            for reratio=0.1:.2:1
                for radii=0.1:.2:1
                    if reratio <= acratio
fismat1=GENFIS2(input,output,radii,[],[squash acratio reratio 0]);
outputchkfuzzy=evalfis(input,fismat1);
numrules11=getfis(fismat1,'numrules');
r_radii1(p)=radii;
s_squash1(p)=squash;
a_acratio1(p)=acratio;
r_reratio1(p)=reratio;
trnRMSE11=norm(outputchkfuzzy-output)/sqrt(length(outputchkfuzzy));
trnRMSE1(p)=norm(outputchkfuzzy-output)/sqrt(length(outputchkfuzzy));
numrules1(p)=numrules11;
kk1=[radii acratio  reratio squash  numrules11 trnRMSE11 ];
fprintf(fid1,'radii1=%4.2f acratio1=%4.2f  reratio1=%4.2f squash1=%4.2f numrules1=%3.0f trnRMSE11=%4.2f  \n',kk1');
p=p+1
      end
   end
end
end
        end
```

Figure A-1: Enumerative search to determine optimal clustering parameters

3. Start the ANFIS editor Graphical User Interface (GUI) by typing “anfisedit” in the MATLAB command line (Figure A-2).

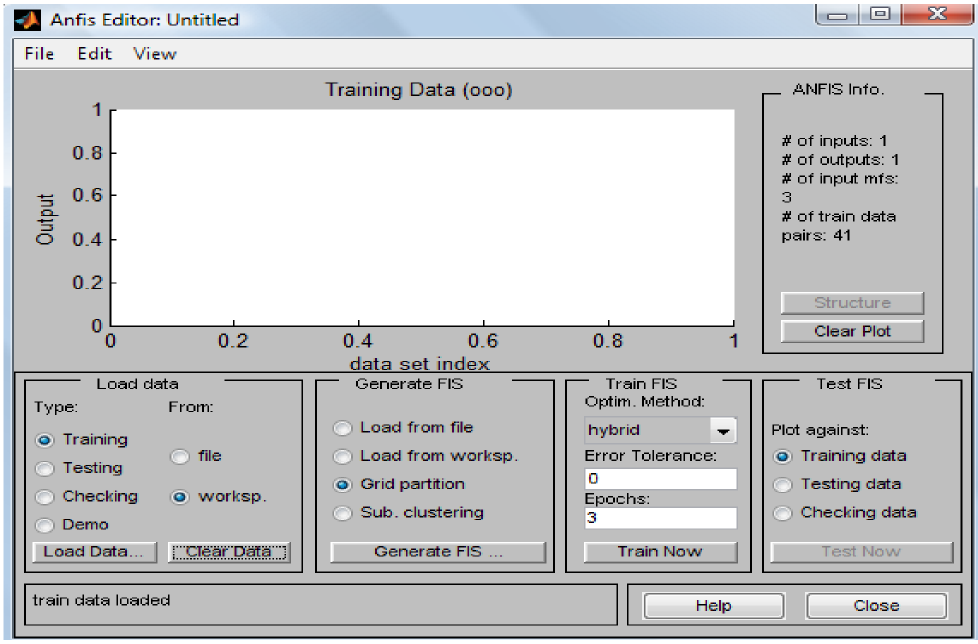


Figure A-2: ANFIS editor GUI

4. Load the step-test data associated with Subject 3 from the workspace by clicking on "load data" button in the ANFIS editor window (Figure A-3).

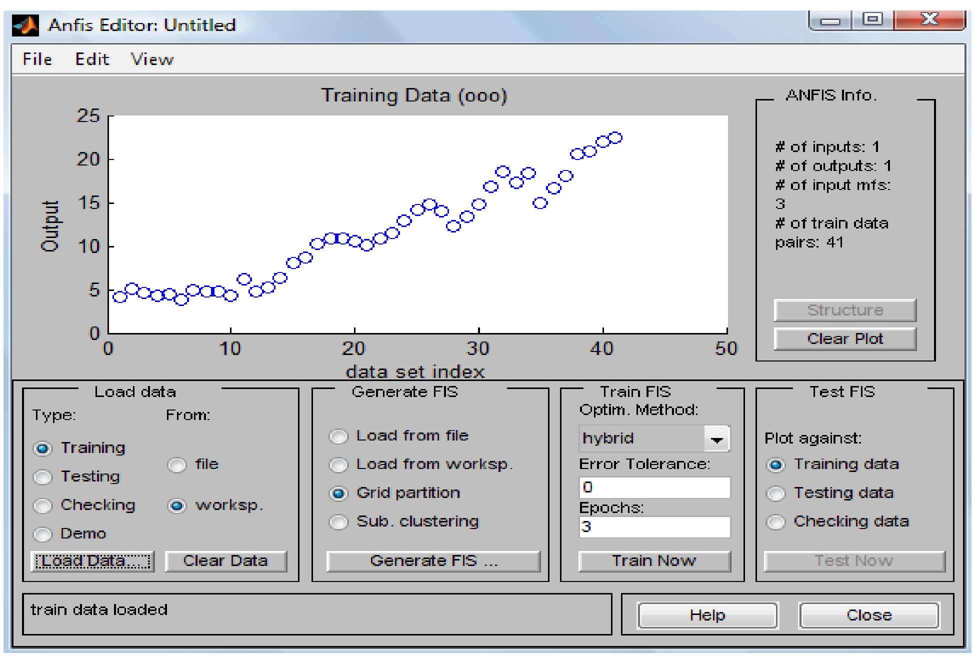


Figure A-3: Step-test data associated with Subject 3

5. Click on the "generate FIS" button on the ANFIS editor and enter the optimal subtractive clustering parameters that were determined in step 2 (Figure A-4).

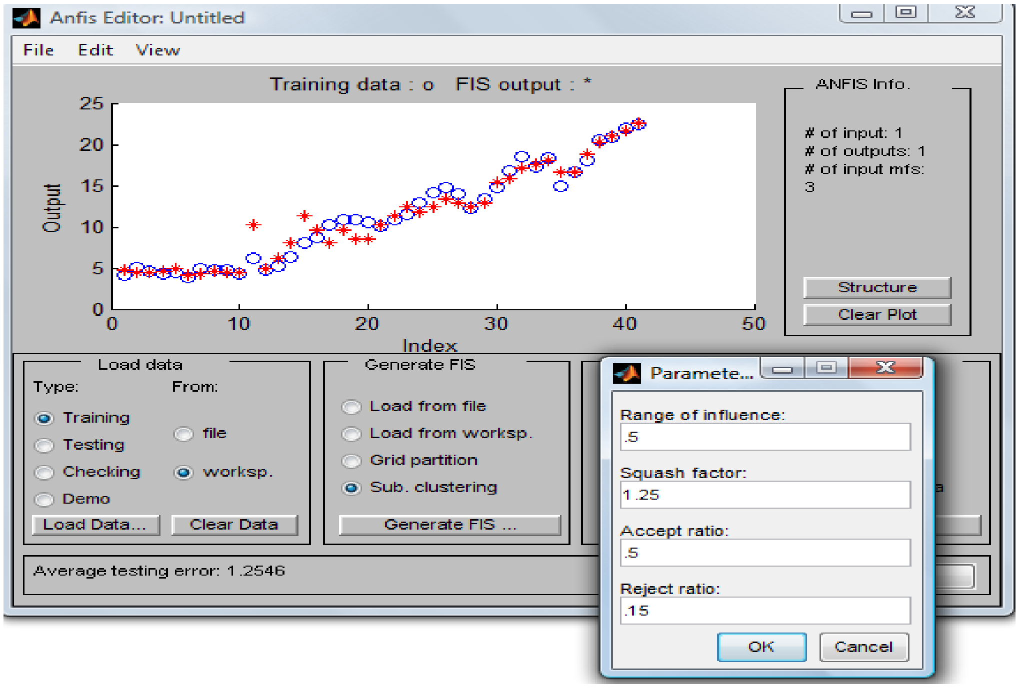


Figure A-4: Initial FIS developed with optimal clustering parameters

6. Optimize the developed FIS by clicking on the “train now” button using a hybrid optimization method.

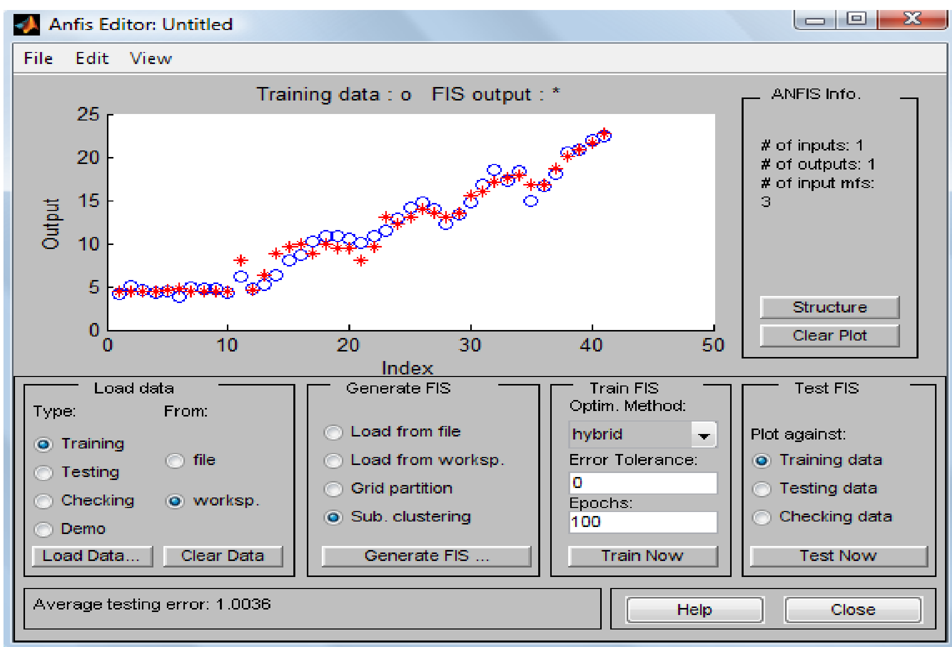


Figure A-5: Optimized FIS (Individual ANFIS)

7. Report the optimized fuzzy IF-THEN rules and Gaussian membership functions associated with Subject 3.

$$IF\ (HR\ is\ A_1)\ THEN\ VO_2 = 0.369 \times HR - 25.9$$
$$IF\ (HR\ is\ A_2)\ THEN\ VO_2 = -0.071 \times HR + 10.48$$
$$IF\ (HR\ is\ A_3)\ THEN\ VO_2 = -1.317 \times HR + 139.2$$

A_1, A_2, and A_3 are the fuzzy sets describing HR associated with rule 1, rule 2, and rule 3, respectively and can be represented by the following Gaussian membership functions:

$$\mu_{A_1}(HR) = e^{-\frac{1}{2}\left(\frac{HR-102.9}{6.45}\right)^2} \qquad (A.1)$$

$$\mu_{A_2}(HR) = e^{-\frac{1}{2}\left(\frac{HR-85.6}{8.39}\right)^2} \qquad (A.2)$$

$$\mu_{A_3}(HR) = e^{-\frac{1}{2}\left(\frac{HR-103.7}{0.88}\right)^2} \qquad (A.3)$$

APPENDIX B – MATLAB code for the General ANFIS model

"Optimizing Subtractive Clustering parameters"

```
--------------------------------------------------------
fid1=fopen('bb.m','w');
load inputtrn.mat;
load outputtrn.mat;
load trn.mat;
load inputchk.mat;
load outputchk;
load chk;

epoch_n=20;
p=1;
 for squash=0.1:.2:1.5
        for acratio=0.1:.2:1
           for reratio=0.1:.2:1
              for radii=0.1:.2:1
                 if reratio <= acratio

fismat1=GENFIS2(inputtrn,outputtrn,radii,[],[squash acratio reratio 0]);
outputchkfuzzy=evalfis(inputchk,fismat1);
numrules11=getfis(fismat1,'numrules');
r_radii1(p)=radii;
s_squash1(p)=squash;
a_acratio1(p)=acratio;
r_reratio1(p)=reratio;

trnRMSE11=norm(outputchkfuzzy-outputchk)/sqrt(length(outputchkfuzzy));
trnRMSE1(p)=norm(outputchkfuzzy-outputchk)/sqrt(length(outputchkfuzzy));
numrules1(p)=numrules11;
kk1=[radii acratio  reratio squash  numrules11 trnRMSE11 ];

fprintf(fid1,'radii1=%4.2f acratio1=%4.2f  reratio1=%4.2f squash1=%4.2f numrules1=%3.0f
trnRMSE11=%4.2f  \n',kk1');

p=p+1
     end
   end
end
end
       end
```

```
save numrules1;
save r_radii1;
save s_squash1;
save a_acratio1;
save r_reratio1;
save trnRMSE1;
save fismat1;


“Generating initial FIS”
------------------------------
fid1=fopen('bb_genfis.m','w');
load inputtrn.mat;
load outputtrn.mat;
load inputchk.mat;
load outputchk.mat;

fismat1=GENFIS2(inputtrn,outputtrn,0.9,[],[1.5 0.9 0.9 0])
fuzout1=evalfis(inputchk,fismat1);
trnRMSE=norm(fuzout1-outputchk)/sqrt(length(fuzout1))

figure
plot(outputchk)
hold on
plot(fuzout1,'r:*')
hold off


“Optimizing FIS parameters”
------------------------------------
fismat2=GENFIS2(inputtrn,outputtrn,0.9,[],[1.5 0.9 0.9 0])
fismat3=ANFIS([inputtrn outputtrn],fismat2,[3 0 0.01])
fuzout2=evalfis(inputchk,fismat3);
trnRMSE=norm(fuzout2-outputchk)/sqrt(length(fuzout2))

figure
plot(outputchk)
hold on
plot(fuzout2,'r:*')
hold off
```

APPENDIX C – General ANFIS model description

The General ANFIS model consists of three fuzzy IF-THEN rules:

$$IF\ (HR\ is\ A_1)\ and\ (HR_{rest}\ is\ B_1) THEN\ VO_2 = 0.4612 \times HR - 0.3555 \times HR_{rest} - 1.388$$

$$IF\ (HR\ is\ A_2)\ and\ (HR_{rest}\ is\ B_2) THEN\ VO_2 = 0.00245 \times HR + 0.2019 \times HR_{rest} + 6.507$$

$$IF\ (HR\ is\ A_3)\ and\ (HR_{rest}\ is\ B_3) THEN\ VO_2 = -0.2483 \times HR - 0.07525 \times HR_{rest} + 24.9$$

A_1, A_2 and A_3 are the fuzzy sets describing the first input (HR) associated with rule 1, rule 2 and rule 3 respectively and can be represented by the following Gaussian membership functions (Figure C-1):

$$\mu_{A_1}(HR) = e^{-\frac{1}{2}\left(\frac{HR-94.03}{19.04}\right)^2} \qquad (C.1)$$

$$\mu_{A_2}(HR) = e^{-\frac{1}{2}\left(\frac{HR-118}{19.07}\right)^2} \qquad (C.2)$$

$$\mu_{A_3}(HR) = e^{-\frac{1}{2}\left(\frac{HR-89.97}{19.16}\right)^2} \qquad (C.3)$$

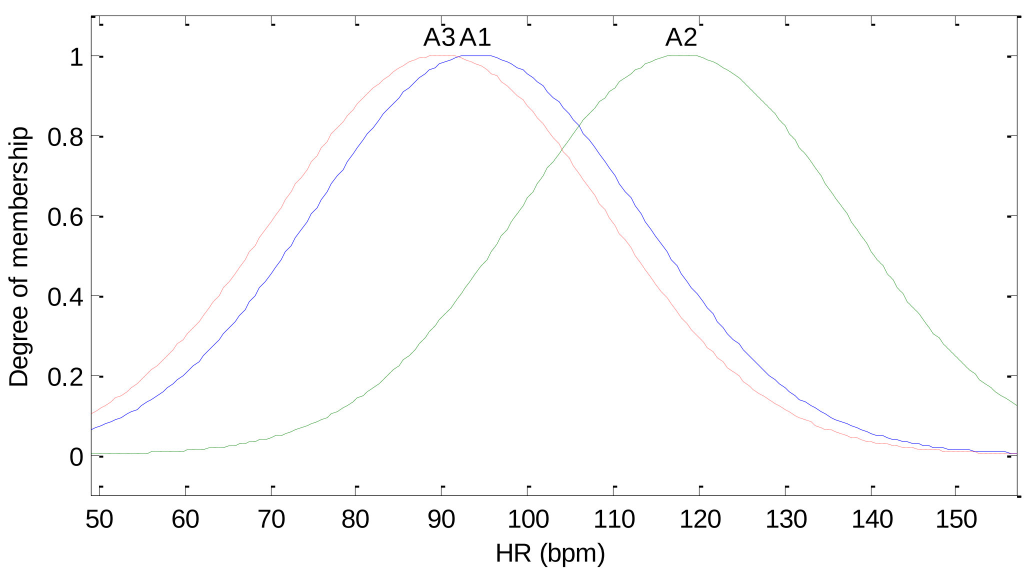


Figure C-1: Optimized Gaussian membership functions associated with HR

B_1, B_2 and B_3 are the fuzzy sets describing the second input (HR_{rest}) associated with rule 1, rule 2 and rule 3 respectively and can be represented by the following Gaussian membership functions (Figure C-2):

$$\mu_{B_1}(HR_{rest}) = e^{-\frac{1}{2}\left(\frac{HR_{rest}-82.86}{6.965}\right)^2} \qquad (C.4)$$

$$\mu_{B_2}(HR_{rest}) = e^{-\frac{1}{2}\left(\frac{HR_{rest}-87.95}{6.695}\right)^2} \qquad (C.5)$$

$$\mu_{B_3}(HR_{rest}) = e^{-\frac{1}{2}\left(\frac{HR_{rest}-89.91}{7.563}\right)^2} \qquad (C.6)$$

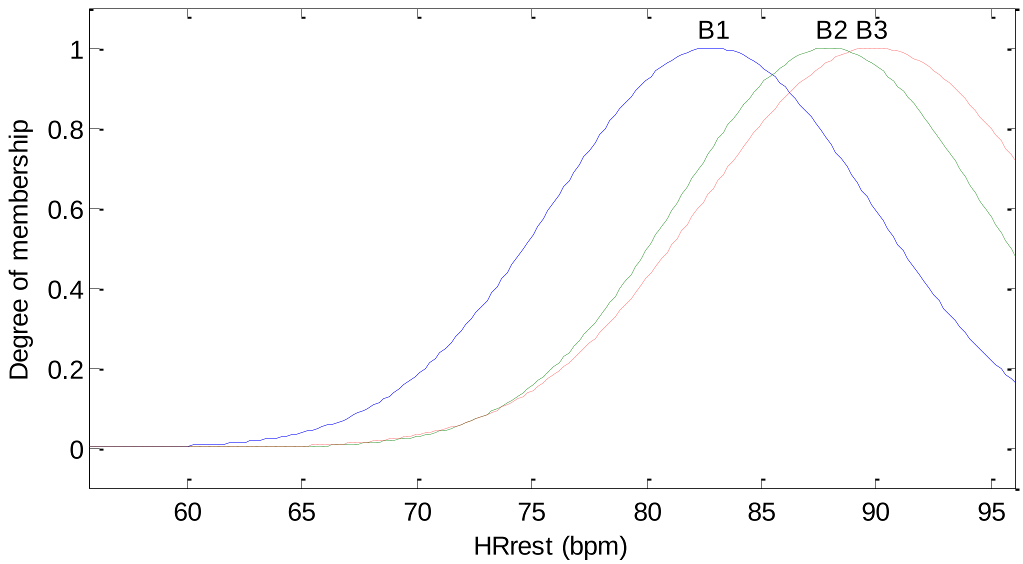


Figure C-2: Optimized Gaussian membership functions associated with HR_{rest}

The architecture of the proposed General ANFIS model with its generated rules is shown in Figure C-3.

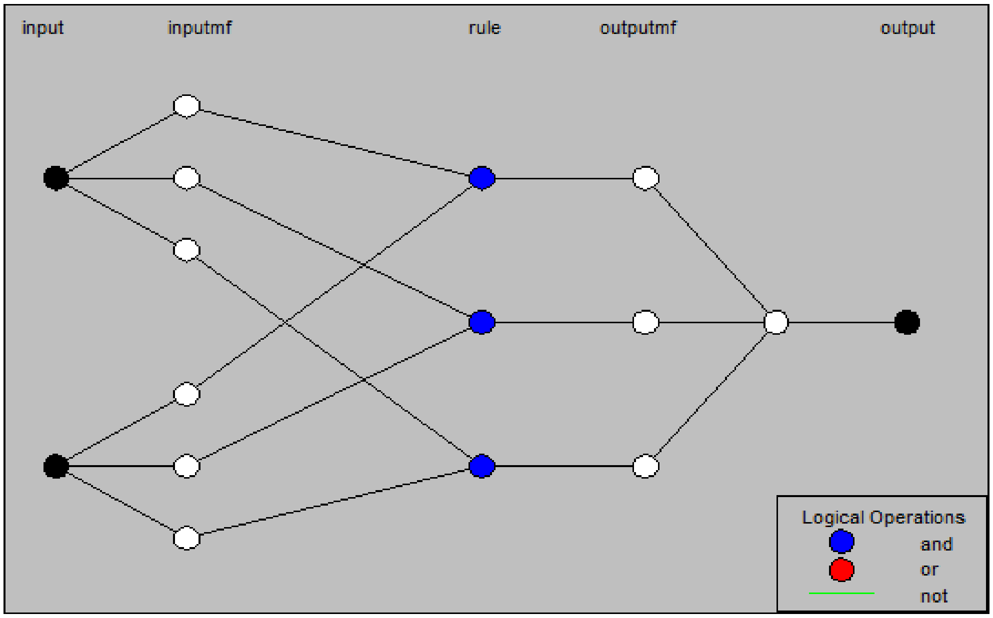


Figure C-3: The General ANFIS architecture

APPENDIX D – General ANFIS model description (trained with all participants)

The General ANFIS model which trained with data obtained from all participants consists of three fuzzy IF-THEN rules:

$$IF\ (HR\ is\ A_1)\ and\ (HR_{rest}\ is\ B_1) THEN\ VO_2 = -0.08169 \times HR - 0.05065 \times HR_{rest} + 11.34$$

$$IF\ (HR\ is\ A_2)\ and\ (HR_{rest}\ is\ B_2) THEN\ VO_2 = 0.6348 \times HR - 1.617 \times HR_{rest} + 98.75$$

$$IF\ (HR\ is\ A_3)\ and\ (HR_{rest}\ is\ B_3) THEN\ VO_2 = 0.4225 \times HR - 0.6512 \times HR_{rest} + 16.75$$

A_1, A_2 and A_3 are the fuzzy sets describing the first input (HR) associated with rule 1, rule 2 and rule 3 respectively and can be represented by the following Gaussian membership functions (Figure D-1):

$$\mu_{A_1}(HR) = e^{-\frac{1}{2}\left(\frac{HR-89.22}{24.75}\right)^2} \qquad (D.1)$$

$$\mu_{A_2}(HR) = e^{-\frac{1}{2}\left(\frac{HR-103.5}{19.12}\right)^2} \qquad (D.2)$$

$$\mu_{A_3}(HR) = e^{-\frac{1}{2}\left(\frac{HR-124}{21.81}\right)^2} \qquad (D.3)$$

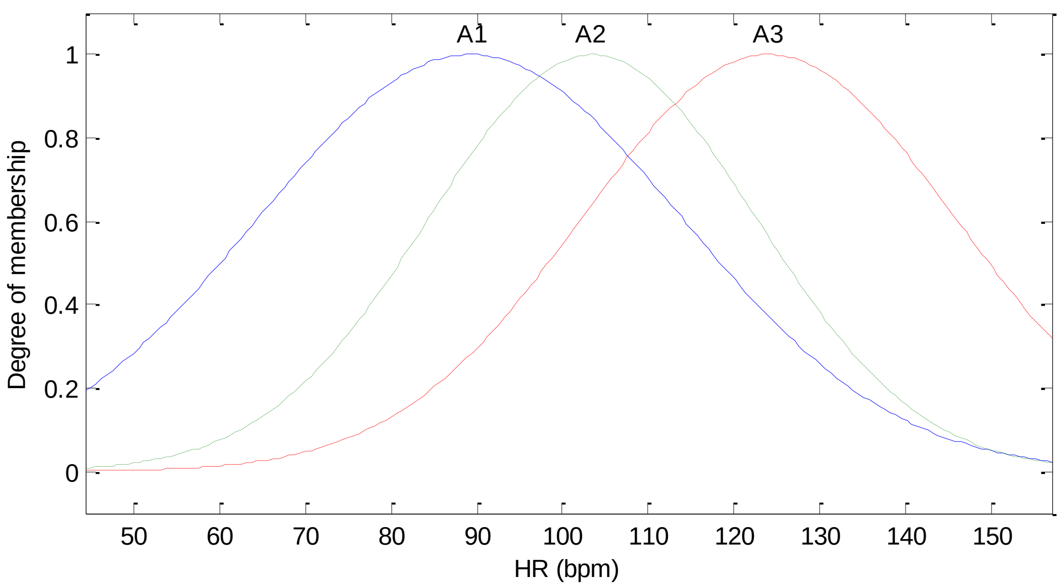


Figure D-1: Optimized Gaussian membership functions associated with HR, trained with all participants

B_1, B_2 and B_3 are the fuzzy sets describing the second input (HR_{rest}) associated with rule 1, rule 2 and rule 3 respectively and can be represented by the following Gaussian membership functions (Figure D-2):

$$\mu_{B_1}(HR_{rest}) = e^{-\frac{1}{2}\left(\frac{HR_{rest}-78.84}{11.02}\right)^2} \quad \text{(D.4)}$$

$$\mu_{B_2}(HR_{rest}) = e^{-\frac{1}{2}\left(\frac{HR_{rest}-92.58}{15.3}\right)^2} \quad \text{(D.5)}$$

$$\mu_{B_3}(HR_{rest}) = e^{-\frac{1}{2}\left(\frac{HR_{rest}-79.02}{7.328}\right)^2} \quad \text{(D.6)}$$

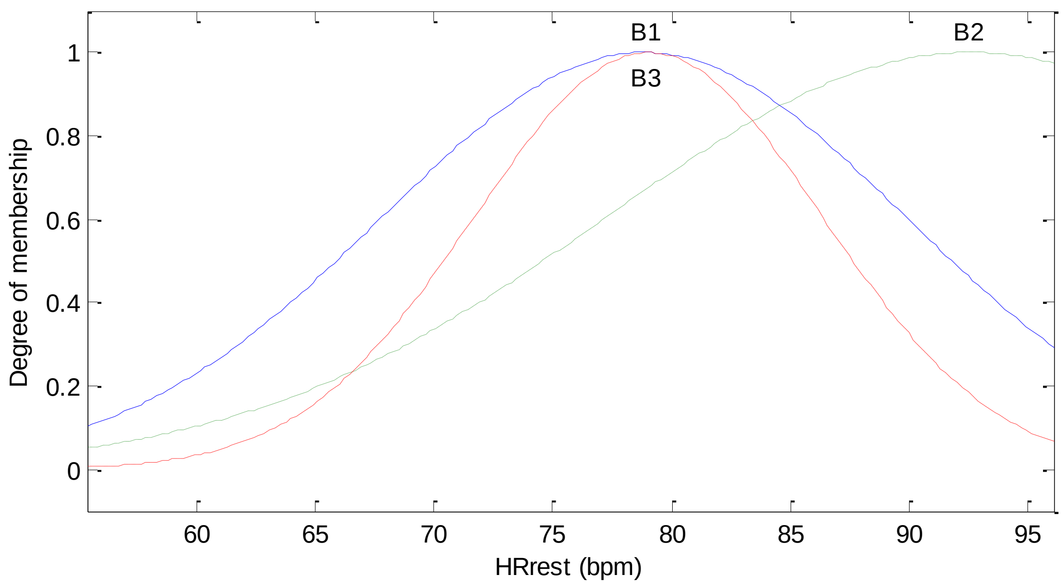


Figure D-2: Optimized Gaussian membership functions associated with HR_{rest}, trained with all participants

The architecture of the proposed General ANFIS model with its generated rules is shown in Figure D-3.

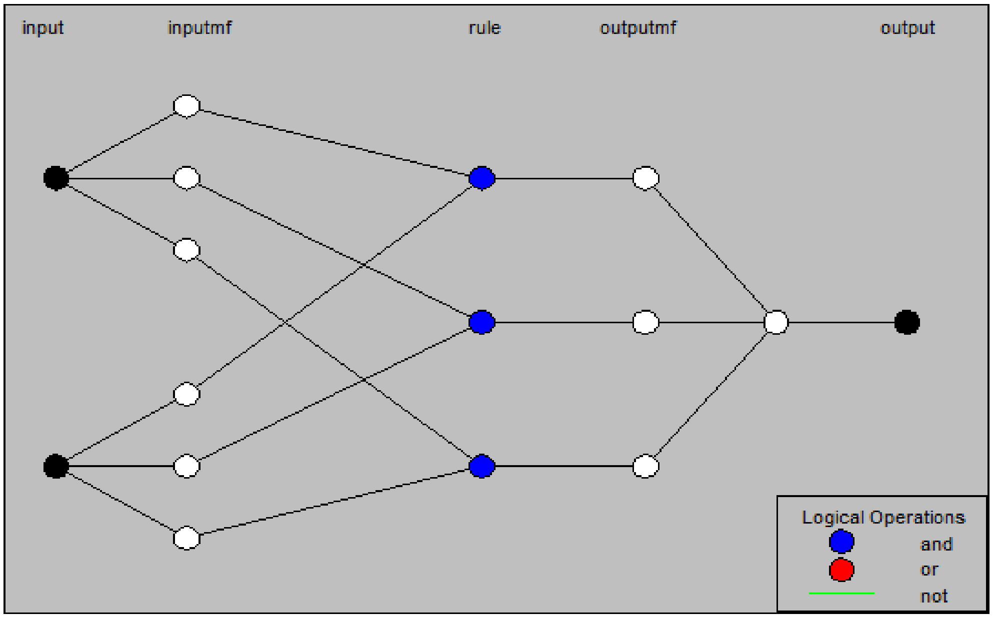


Figure D-3: The General ANFIS architecture after training with all participants

APPENDIX E – Implementing the General ANFIS model using Excel

Once the General ANFIS model has been developed using MATLAB (Appendix D), it can be implemented in Excel as a decision-making tool, following five main steps:

1. Determine inputs and associated membership functions for the General ANFIS model.

The first step is to determine the variables to be input into the model (i.e., HR and HR_{rest}), where HR ≥ HR_{rest}. Then, define the predetermined Gaussian membership functions for each input variable (Eqs. (C.1), …, (C.6)) using the "Exp ()" function provided in Excel.

Insert an individual's HR

Input 1	HR		bpm

Fuzzy sets associated with HR

	μ	σ
A1	89.22	24.75
A2	103.5	19.12
A3	124	21.81

Insert an individual's HR_{rest}

Input 2	HR_{rest}		bpm

Fuzzy sets associated with HR_{rest}

	μ	σ
B1	78.84	11.02
B2	92.58	15.3
B3	79.02	7.328

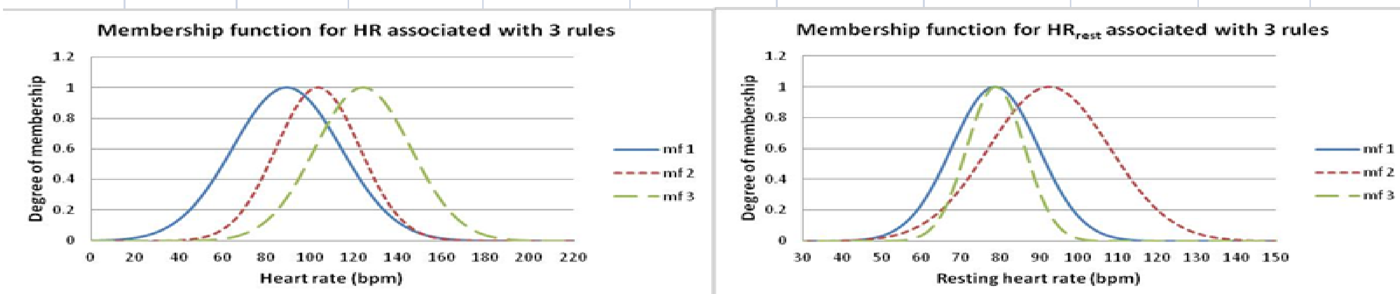


Figure E-1: Defining the membership functions (mf) associated with HR and HR_{rest} in Excel

2. Fuzzify the input variables associated with the General ANFIS model.

In the fuzzification process, the degree to which each input variable belongs to each of the associated fuzzy sets is determined using the predetermined membership functions. This yields a fuzzified value for each input variable between 0 and 1 (Figure E-2).

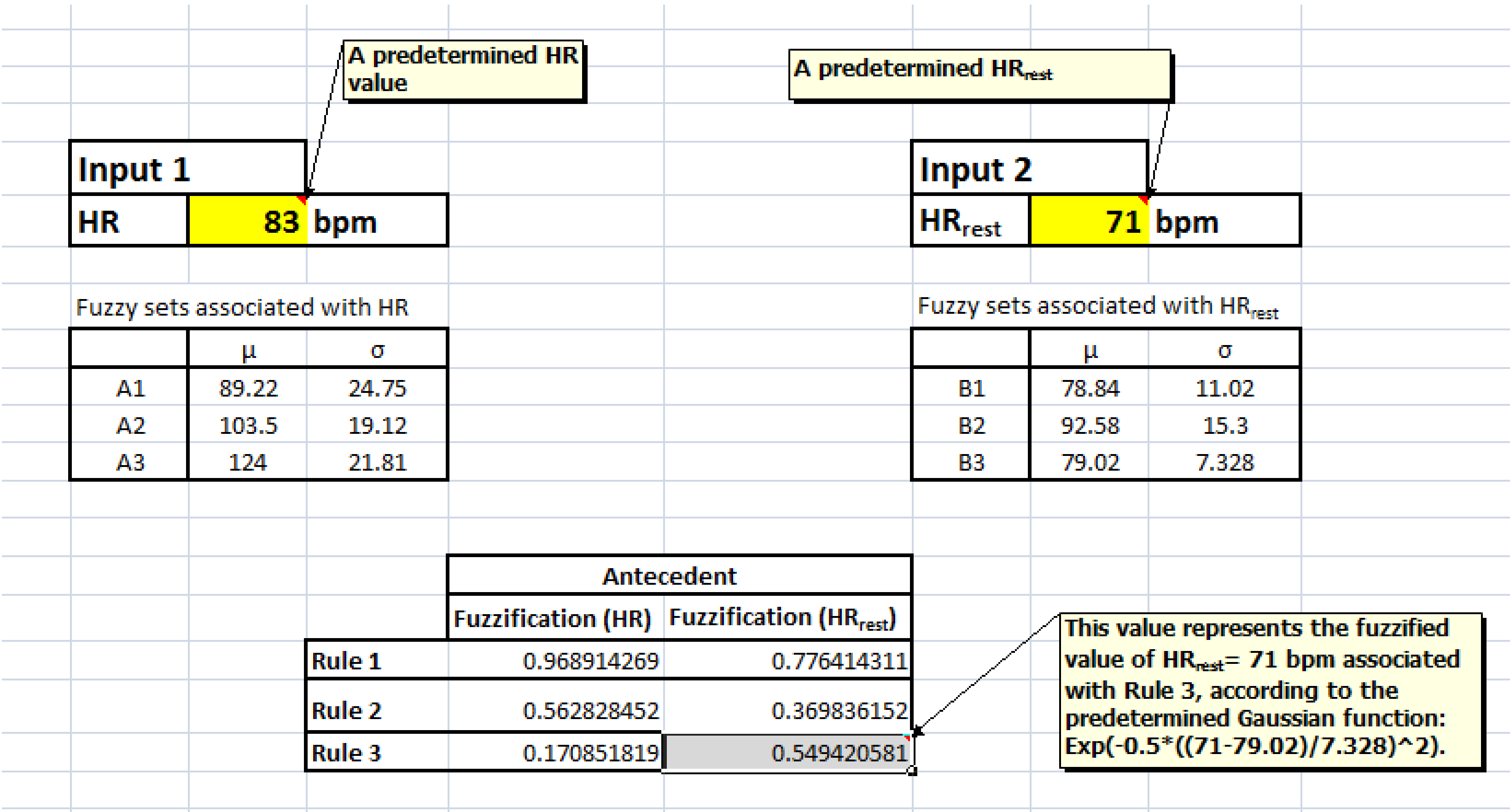


Figure E-2: Fuzzification of predetermined input variables

3. Determine the firing strength of each rule associated with the General ANFIS model

Fuzzifying the input variables yields the degree to which each input variable is satisfied for each rule. Because there are more than one input variable in the antecedent of the rules, the fuzzy operator (i.e., product) is used to obtain a number (the firing strength) associated with the antecedent of each rule (Figure E-3).

Input 1		
HR	83	bpm

Input 2		
HR_{rest}	71	bpm

Fuzzy sets associated with HR

	μ	σ
A1	89.22	24.75
A2	103.5	19.12
A3	124	21.81

Fuzzy sets associated with HR_{rest}

	μ	σ
B1	78.84	11.02
B2	92.58	15.3
B3	79.02	7.328

	Antecedent		
	Fuzzification (HR)	Fuzzification (HR_{rest})	Fuzzy operator (product)
Rule 1	0.968914269	0.776414311	0.752278905
Rule 2	0.562828452	0.369836152	0.208154309
Rule 3	0.170851819	0.549420581	0.093869506

This value represents a single antecedent value (firing strength) associated with Rule 3, which was calculated according to the product operator: (0.170851819) x (0.549420581).

Figure E-3: Firing strength of each rule associated with the General ANFIS model

4. Determine the weighted output of each rule associated with the General ANFIS model.

The consequent (output) of a fuzzy rule is calculated as a function of the input variables. The output value is then rescaled using the firing strength of that rule. This process (implication) is applied to each rule using the product method (Figure E-4).

Input 1		
HR	83	bpm

Input 2		
HR_{rest}	71	bpm

Fuzzy sets associated with HR

	μ	σ
A1	89.22	24.75
A2	103.5	19.12
A3	124	21.81

Fuzzy sets associated with HR_{rest}

	μ	σ
B1	78.84	11.02
B2	92.58	15.3
B3	79.02	7.328

	Antecedent		→	Consequent	
	Fuzzification (HR)	Fuzzification (HR_{rest})	Fuzzy operator (product)	Unweighted	Weighted
Rule 1	0.968914269	0.776414311	0.752278905	0.96358	0.72488091
Rule 2	0.562828452	0.369836152	0.208154309	36.6314	7.62498376
Rule 3	0.170851819	0.549420581	0.093869506	5.5823	0.52400774

This value represents the value of the consequent associated with Rule 3, which was determined using the first-order polynomial in terms of HR (83 bpm) and HR_{rest} (71 bpm), see Rule 3 in Appendix C: 0.4225x(83) - 0.6512x(71) + 16.75.

This value represents the weighted value of the consequent associated with Rule 3 using the product implication method: (5.5823)x(0.093869506).

Figure E-4: Weighted output associated with each rule of the General ANFIS model

5. Aggregate the consequents across all rules for the General ANFIS model.

The final aggregated output of the General ANFIS model is calculated as the weighted average of all the rules' outputs (Figure E-5).

Input 1		
HR	**83**	**bpm**

Input 2		
HR_{rest}	**71**	**bpm**

Fuzzy sets associated with HR

	μ	σ
A1	89.22	24.75
A2	103.5	19.12
A3	124	21.81

Fuzzy sets associated with HR_{rest}

	μ	σ
B1	78.84	11.02
B2	92.58	15.3
B3	79.02	7.328

	Antecedent			**Consequent**	
	Fuzzification (HR)	**Fuzzification (HR_{rest})**	**Fuzzy operator (product)**	**Unweighted**	**Weighted**
Rule 1	0.968914269	0.776414311	0.752278905	0.96358	0.724881
Rule 2	0.562828452	0.369836152	0.208154309	36.6314	7.624984
Rule 3	0.170851819	0.549420581	0.093869506	5.5823	0.524008

Estimated VO_2	
8.417	**ml/kg.min**

This value is calculated as the sum of all weighted outputs/sum of all firing strengths.

Figure E-5: Estimated VO_2 by the General ANFIS model

APPENDIX F – Combined backward selection method and 10-fold cross validation

1. Randomly assign the learning set to each of 10 equal-sized partitions such that at each partition, 9 different folds are used as the training set while the remaining fold is used as the validation set.
2. For each partition, develop an initial fuzzy model using the training set and incorporating the set of all possible input variables.
3. For each partition, assess the performance (i.e., RMSE) of the developed initial fuzzy model using the validation set.
4. Compute the average performance (i.e., average RMSE) of the developed initial fuzzy models over all 10 partitions.
5. For each partition, temporarily remove each input variable from the set of possible input variables, one at a time from the rule-base of the fuzzy model and assess the performance (i.e., RMSE) of the resultant truncated fuzzy models using the validation set.
6. Compute the average performance (i.e., average RMSE) of the truncated fuzzy models over all 10 partitions.
7. If there is improvement over a previous level, permanently remove the input variable associated with the best average performance obtained in step 6. Identify the best set of input variables associated with the best truncated fuzzy model and its corresponding performance. If there is no improvement, go to step 9.
8. If there is another input variable remaining in the best truncated fuzzy model, go to step 5. Otherwise, go to step 9.
9. Of the developed initial fuzzy model and the winner truncated fuzzy models, select the set of input variables associated with best average performance (lowest average RMSE).
10. Train the fuzzy model (with best average performance) using the whole learning set and call it ANFIS module.

APPENDIX G – The three ANFIS modules developed in this study

The ANFIS module 1 concerned with estimating VO_2 rest consists of the following two fuzzy IF-THEN rules:

$$If\ Age\ is\ A_1\ AND\ Weight\ is\ B_1\ AND\ Height\ is\ C_1\ AND\ HR_{rest}\ is\ E_1\ THEN\ VO_2rest = -0.08573 \times Age + 0.006192 \times Weight - 0.04436 \times Height + 0.01861 \times HR_{rest} + 13.42$$

$$If\ Age\ is\ A_2\ AND\ Weight\ is\ B_2\ AND\ Height\ is\ C_2\ AND\ HR_{rest}\ is\ E_2\ THEN\ VO_2rest = -0.1122 \times Age - 0.01374 \times Weight - 0.0826 \times Height + 0.06263 \times HR_{rest} + 23.57$$

$A_i, B_i, C_i\ and\ E_i$ are fuzzy sets describing the age, weight, height and HR_{rest}, respectively where i corresponds to the number of rules. These fuzzy sets were represented by Gaussian membership functions (Table G.1).

Table G.1: Optimized parameters of the Gaussian membership functions describing the fuzzy sets associated with ANFIS module 1

Fuzzy rule-base	**A_i (years)**		**B_i (kg)**		**C_i (cm)**		**E_i (bpm)**	
	μ_{A_i}	σ_{A_i}	μ_{B_i}	σ_{B_i}	μ_{C_i}	σ_{C_i}	μ_{E_i}	σ_{E_i}
Rule 1	45.987	7.051	78.873	8.907	172.98	5.772	64.131	6.618
Rule 2	57.942	7.167	77.666	9.175	175.23	5.146	60.628	7.257

Note. A_i: fuzzy sets of age associated with Rule i (i = 1, 2); B_i: fuzzy sets of weight associated with Rule i (i = 1, 2); C_i: fuzzy sets of height associated with Rule i (i = 1, 2); E_i: fuzzy sets of HR_{rest} associated with Rule i (i = 1, 2).

The ANFIS module 2 concerned with estimating the Flex point consists of the following five fuzzy IF-THEN rules:

$$If\ Weight\ is\ B_1\ AND\ BMI\ is\ D_1\ AND\ HR_{rest}\ is\ E_1\ THEN\ Flex\ point = 0.49486 \times Weight - 0.62623 \times BMI + 1.7211 \times HR_{rest} - 71.225$$

$$If\ Weight\ is\ B_2\ AND\ BMI\ is\ D_2\ AND\ HR_{rest}\ is\ E_2\ THEN\ Flex\ point = 0.53089 \times Weight + 0.64567 \times BMI + 1.0255 \times HR_{rest} - 41.181$$

$$If\ Weight\ is\ B_2\ AND\ BMI\ is\ D_2\ AND\ HR_{rest}\ is\ E_2\ THEN\ Flex\ point = -0.34443 \times Weight + 0.46353 \times BMI + 0.83388 \times HR_{rest} + 44.001$$

$$If\ Weight\ is\ B_2\ AND\ BMI\ is\ D_2\ AND\ HR_{rest}\ is\ E_2\ THEN\ Flex\ point = -0.078132 \times Weight - 1.9512 \times BMI + 1.3141 \times HR_{rest} + 37.66$$

$$If\ Weight\ is\ B_2\ AND\ BMI\ is\ D_2\ AND\ HR_{rest}\ is\ E_2\ THEN\ Flex\ point = -0.35439 \times Weight + 0.73869 \times BMI + 1.5339 \times HR_{rest} - 19.538$$

$B_i, D_i\ and\ E_i$ are fuzzy sets describing the weight, BMI and HR_{rest}, respectively where i corresponds to the number of rules. The parameters describing the Gaussian membership functions associated with the fuzzy sets are presented in Table G.2.

Table G.2: Optimized parameters of the Gaussian membership functions describing the fuzzy sets associated with ANFIS module 2

Fuzzy rule-base	$\boldsymbol{B_i}$ **(kg)**		$\boldsymbol{D_i}$ **(kg.m^{-2})**		$\boldsymbol{E_i}$ **(bpm)**	
	$\boldsymbol{\mu_{B_i}}$	$\boldsymbol{\sigma_{B_i}}$	$\boldsymbol{\mu_{D_i}}$	$\boldsymbol{\sigma_{D_i}}$	$\boldsymbol{\mu_{E_i}}$	$\boldsymbol{\sigma_{E_i}}$
Rule 1	70.761	5.393	23.648	1.436	85	4.137
Rule 2	77.61	5.393	25.264	1.436	60.5	4.137
Rule 3	95.709	5.393	28.614	1.436	68.5	4.137
Rule 4	68.04	5.393	24.135	1.436	76	4.137
Rule 5	81.602	5.393	27.351	1.436	65.222	4.137

Note. B_i: fuzzy sets of weight associated with Rule i (i = 1, …, 5); D_i: fuzzy sets of BMI associated with Rule i (i = 1, …, 5); E_i: fuzzy sets of HR_{rest} associated with Rule i (i = 1, …, 5).

The ANFIS module 3 concerned with estimating the slope and intercept of the linear VO_2-HR curve above the Flex point consists of the following two fuzzy IF-THEN rules:

$$If\ Age\ is\ A_1 AND\ Weight\ is\ B_1\ AND\ Height\ is\ C_1\ AND\ BMI\ is\ D_1\ AND\ HR_{rest}\ is\ E_1\ THEN\ (Slope = 0.0001404 \times Age + 0.01286 \times Weight - 0.005011 \times Height - 0.04247 \times BMI - 0.000551 \times HR_{rest} + 1.329)$$

AND

$$(Intercept = -0.07412 \times Age - 2.193 \times Weight + 1.33 \times Height + 6.547 \times BMI - 0.2555 \times HR_{rest} - 225.3)$$

$$If\ Age\ is\ A_1 AND\ Weight\ is\ B_1\ AND\ Height\ is\ C_1\ AND\ BMI\ is\ D_1\ AND\ HR_{rest}\ is\ E_1\ THEN$$

$$(Slope = -0.004977 \times Age + 0.01052 \times Weight - 0.01834 \times Height - 0.05628 \times BMI + 0.003263 \times HR_{rest} + 4.208)$$

AND

$$(Intercept = 0.4359 \times Age + 0.06665 \times Weight + 0.5215 \times Height + 1.501 \times BMI - 0.5238 \times HR_{rest} - 139.3)$$

Table G.3 presents the parameters describing the Gaussian membership functions associated with the fuzzy sets $A_i, B_i, C_i, D_i\ and\ E_i$.

Table G.3: Optimized parameters of the Gaussian membership functions describing the fuzzy sets associated with ANFIS module 3

Rule-base	$\boldsymbol{A_i}$ **(years)**		$\boldsymbol{B_i}$ **(kg)**		$\boldsymbol{C_i}$ **(cm)**		$\boldsymbol{D_i}$ **(kg.min^{-2})**		$\boldsymbol{E_i}$ **(bpm)**	
	μ_{A_i}	σ_{A_i}	μ_{B_i}	σ_{B_i}	μ_{C_i}	σ_{C_i}	μ_{D_i}	σ_{D_i}	μ_{E_i}	σ_{E_i}
Rule 1	42	4.35	73.85	5.393	177	3.29	23.56	1.44	67.75	4.14
Rule 2	43	4.35	78.02	5.39	177.8	3.29	24.68	1.44	64.08	4.14

Note. A_i: fuzzy sets of age associated with Rule i (i = 1, 2); B_i: fuzzy sets of weight associated with Rule i (i = 1, 2); C_i: fuzzy sets of height associated with Rule i (i = 1, 2); D_i: fuzzy sets of BMI associated with Rule i (i = 1, 2); E_i: fuzzy sets of HR_{rest} associated with Rule i (i = 1, 2).

APPENDIX H – Implementing the ANFIS prediction model using Excel

Once the ANFIS prediction model has been developed using MATLAB (Appendix G), it can be implemented in Excel as a decision-making tool, following six main steps:

1. Determine the input variables and associated membership functions for each ANFIS module.

The first step is to determine the variables to be input into the ANFIS module 1 (age, weight, height, and HR_{rest}), ANFIS module 2 (weight, BMI, and HR_{rest}), and ANFIS module 3 (age, weight, height, BMI, and HR_{rest}). Then, define the predetermined Gaussian membership functions for each input variable using the "Exp ()" function provided in Excel.

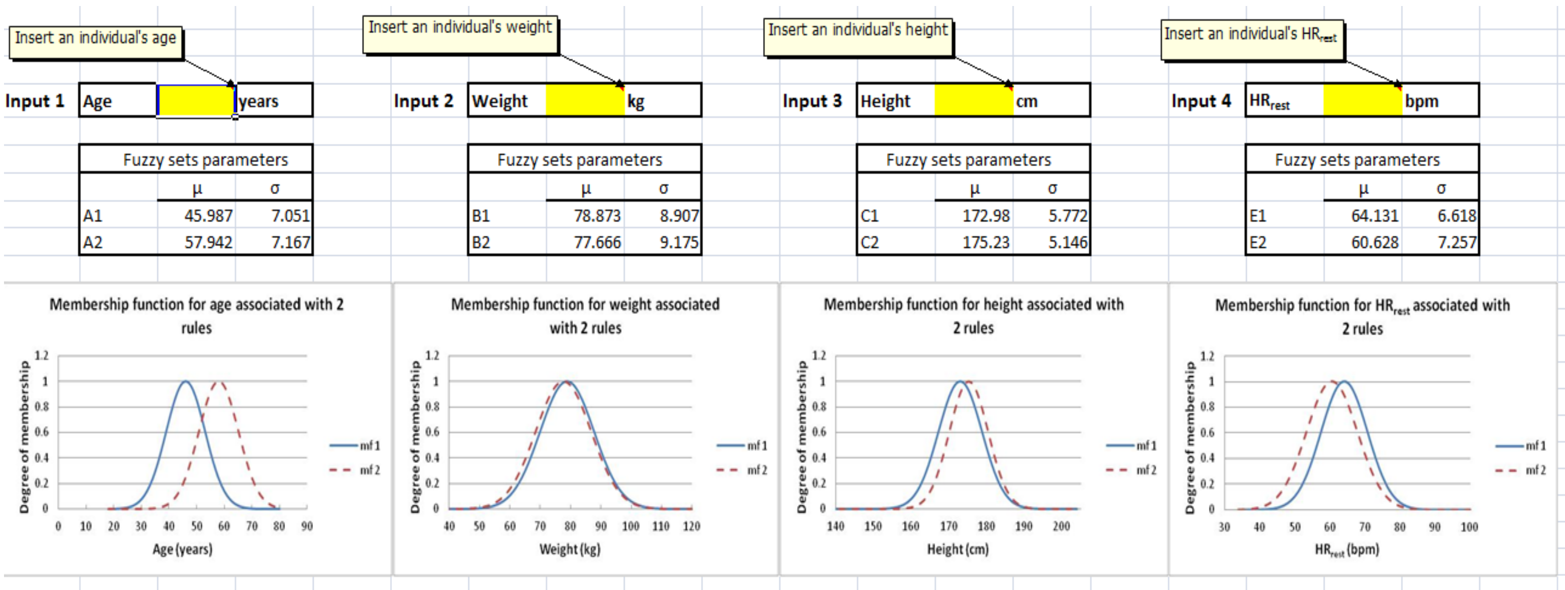


Figure H-1: ANFIS module 1: input variables and membership functions definition

Insert individual's weight

Input 1	Weight		kg

Fuzzy sets parameters		
	μ	σ
B1	70.761	5.393
B2	77.61	5.393
B3	95.709	5.393
B4	68.04	5.393
B5	81.602	5.393

Insert individual's BMI

Input 2	BMI		kg/m^2

Fuzzy sets parameters		
	μ	σ
D1	23.648	1.436
D2	25.264	1.436
D3	28.64	1.436
D4	24.135	1.436
D5	27.351	1.436

Insert individual's HR_{rest}

Input 3	HR_{rest}		bpm

Fuzzy sets parameters		
	μ	σ
E1	85	4.137
E2	60.5	4.137
E3	68.5	4.137
E4	76	4.137
E5	65.222	4.137

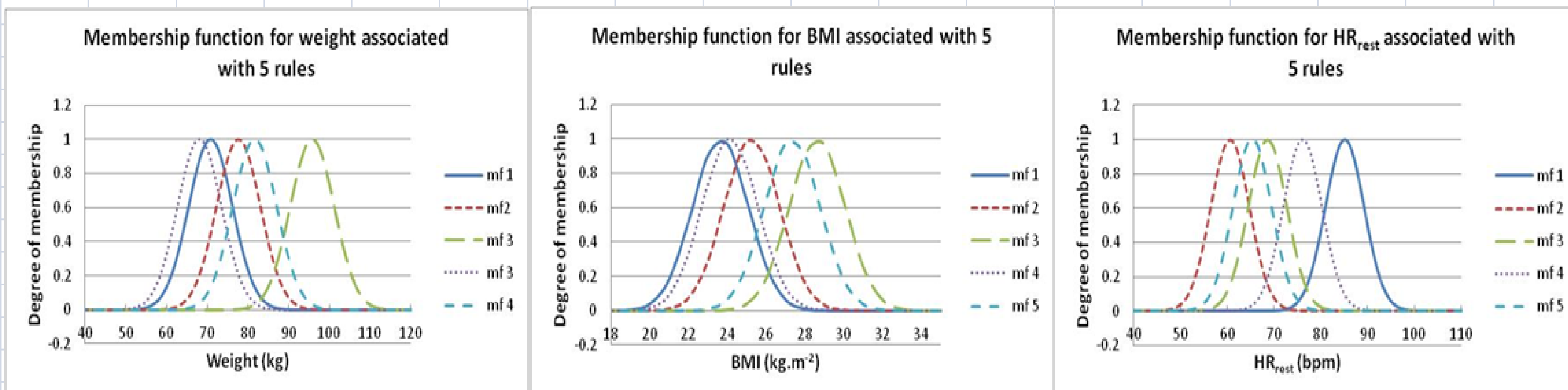


Figure H-2: ANFIS module 2: input variables and membership functions definition

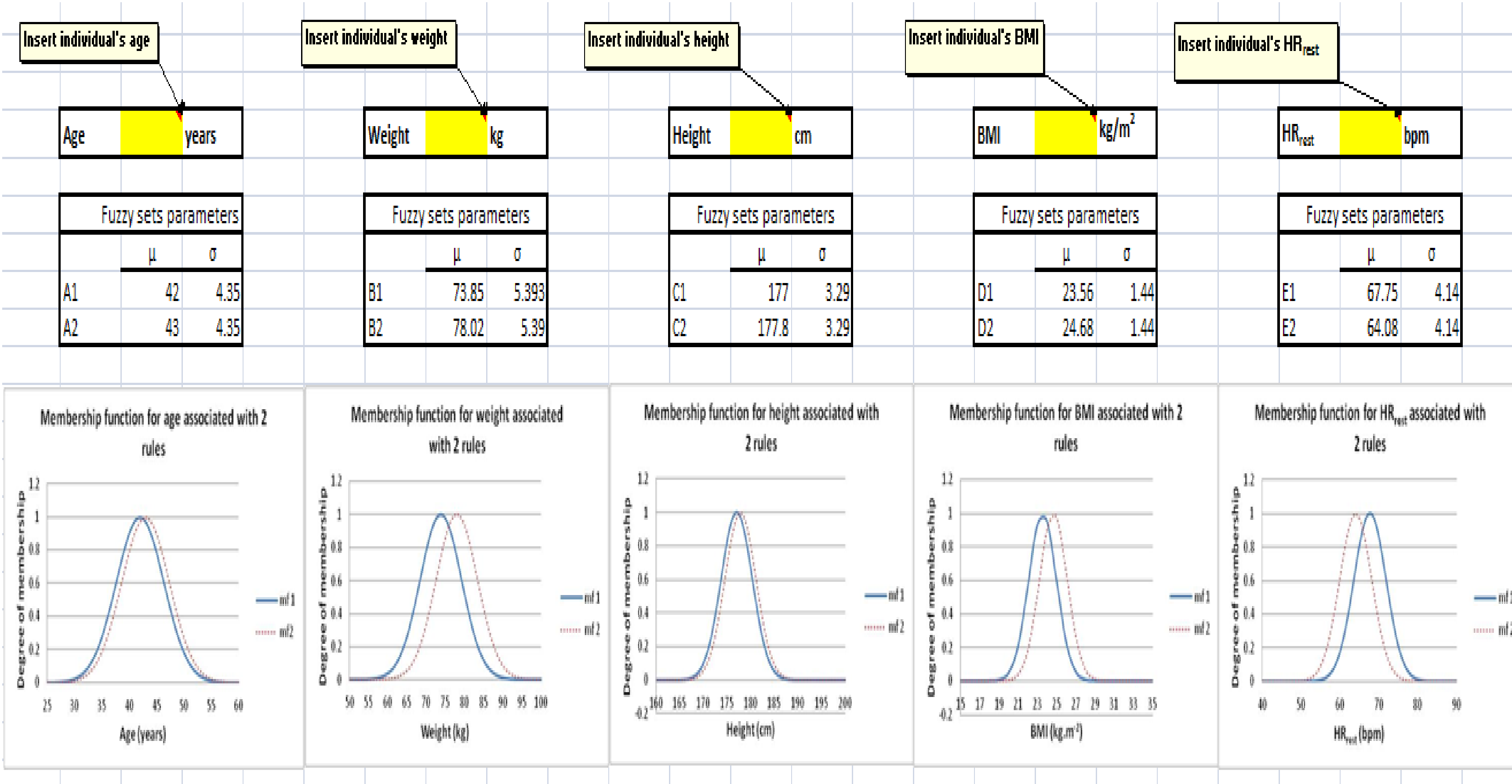


Figure H-3: ANFIS module 3: input variables and membership functions definition

2. Fuzzify the input variables associated with each ANFIS module.

In the fuzzification process, the degree to which each input variable belongs to each of the associated fuzzy sets is determined using the predetermined membership functions. This yields a fuzzified value for each input variable between 0 and 1 (Figure H-4).

Age= 23 years	Weight= 77.15 kg	Height= 175 cm	BMI= 25.19 kg/m^2	HR_{rest}= 57.17 bpm

Predetermined input variables

ANFIS module 1

Fuzzy sets parameters			Fuzzy sets parameters			Fuzzy sets parameters						Fuzzy sets parameters		
	μ	σ		μ	σ		μ	σ					μ	σ
A1	45.987	7.051	B1	78.873	8.907	C1	172.98	5.772				E1	64.131	6.618
A2	57.942	7.167	B2	77.666	9.175	C2	175.23	5.146				E2	60.628	7.257

	Antecedent			
	Fuzzification (Age)	Fuzzification (Weight)	Fuzzification (Height)	Fuzzification (HRrest)
Rule 1	0.004921499	0.981463782	0.94059947	0.57512295
Rule 2	6.89463E-06	0.998419793	0.999001681	0.89267856

ANFIS module 2

			Fuzzy sets parameters						Fuzzy sets parameters			Fuzzy sets parameters		
				μ	σ					μ	σ		μ	σ
			B1	70.761	5.393				D1	23.648	1.436	E1	85	4.137
			B2	77.61	5.393				D2	25.264	1.436	E2	60.5	4.137
			B3	95.709	5.393				D3	28.64	1.436	E3	68.5	4.137
			B4	68.04	5.393				D4	24.135	1.436	E4	76	4.137
			B5	81.602	5.393				D5	27.351	1.436	E5	65.222	4.137

	Antecedent		
	Fuzzification (Weight)	Fuzzification (BMI)	Fuzzification (HRrest)
Rule 1	0.495723032	0.561067048	1.49024E-10
Rule 2	0.996368926	0.998738116	0.72328131
Rule 3	0.002681666	0.055969537	0.023512159
Rule 4	0.24008949	0.762755591	3.17199E-05
Rule 5	0.711245841	0.322904118	0.150451326

This value represents the fuzzified value of HRrest = 57.17 bpm associated with Rule 5 of ANFIS module 2, according to the predetermined Gaussian function: Exp(-0.5*((57.17-65.222)/4.137)^2).

ANFIS module 3

Fuzzy sets parameters			Fuzzy sets parameters			Fuzzy sets parameters			Fuzzy sets parameters			Fuzzy sets parameters		
	μ	σ		μ	σ		μ	σ		μ	σ		μ	σ
A1	42	4.35	B1	73.85	5.393	C1	177	3.29	D1	23.56	1.44	E1	67.75	4.14
A2	43	4.35	B2	78.02	5.39	C2	177.8	3.29	D2	24.68	1.44	E2	64.08	4.14

	Antecedent				
	Fuzzification (Age)	Fuzzification (Weight)	Fuzzification (Height)	Fuzzification (BMI)	Fuzzification (HRrest)
Rule 1	7.19954E-05	0.829266712	0.831293076	0.52618957	0.038180434
Rule 2	2.56895E-05	0.987057882	0.696174577	0.93878427	0.248349669

Figure H-4: Fuzzification of predetermined input variables

3. Determine the firing strength of each rule associated with each ANFIS module

Fuzzifying the input variables yields the degree to which each input variable is satisfied for each rule. Because there are more than one input variable in the antecedent of the rules, the fuzzy operator (i.e., product) is used to obtain a number (the firing strength) associated with the antecedent of each rule (Figure H-5).

ANFIS module 1

Rule base	Antecedent				
	Fuzzification (Age)	Fuzzification (Weight)	Fuzzification (Height)	Fuzzification (HR_{rest})	Firing strength
Rule 1	0.004921499	0.981463782	0.94059947	0.57512295	0.002612986
Rule 2	6.89463E-06	0.998419793	0.999001681	0.89267856	6.13883E-06

ANFIS module 2

Rule base	Antecedent			
	Fuzzification (Weight)	Fuzzification (BMI)	Fuzzification (HR_{rest})	Firing strength
Rule 1	0.495723032	0.561067048	1.49024E-10	4.14485E-11
Rule 2	0.996368926	0.998738116	0.72328131	0.719745639
Rule 3	0.002681666	0.055969537	0.023512159	3.52898E-06
Rule 4	0.24008949	0.762755591	3.17199E-05	5.80886E-06
Rule 5	0.711245841	0.322904118	0.150451326	0.034553285

This value represents a single antecedent value (firing strength) associated with Rule 5 of ANFIS module 2, which was calculated according to the product operator: (0.711245841) x (0.322904118) x (0.1504513).

ANFIS module 3

Rule base	Antecedent					
	Fuzzification (Age)	Fuzzification (Weight)	Fuzzification (Height)	Fuzzification (BMI)	Fuzzification (HR_{rest})	Firing strength
Rule 1	7.19954E-05	0.829266712	0.831293076	0.52618957	0.038180434	9.97094E-07
Rule 2	2.56895E-05	0.987057882	0.696174577	0.93878427	0.248349669	4.11572E-06

Figure H-5: Firing strength of each rule associated with ANFIS modules

4. Determine the weighted output of each rule associated with each ANFIS module.

The consequent (output) of a fuzzy rule is calculated as a function of the input variables. The output value is then rescaled using the firing strength of that rule. This process (implication) is applied to each rule using the product method (Figure H-6).

ANFIS module 1

Rule base	Antecedent					Consequent	
	Fuzzification (Age)	Fuzzification (Weight)	Fuzzification (Height)	Fuzzification (HR_{rest})	Firing strength	Unweighted	Weighted
Rule 1	0.004921499	0.981463782	0.94059947	0.57512295	0.002612986	5.2268565	0.013657703
Rule 2	6.89463E-06	0.998419793	0.999001681	0.89267856	6.13883E-06	9.0549161	5.55865E-05

ANFIS module 2

Rule base	Antecedent				Consequent	
	Fuzzification (Weight)	Fuzzification (BMI)	Fuzzification (HR_{rest})	Firing strength	Unweighed	Weighted
Rule 1	0.495723032	0.561067048	1.49024E-10	4.14485E-11	49.57285208	2.05472E-09
Rule 2	0.996368926	0.998738116	0.72328131	0.719745639	74.67061172	53.74384714
Rule 3	0.002681666	0.055969537	0.023512159	3.52898E-06	29.93927758	0.000105655
Rule 4	0.24008949	0.762755591	3.17199E-05	5.80886E-06	57.60490136	0.000334619
Rule 5	0.711245841	0.322904118	0.150451326	0.034553285	59.42283238	2.053254072

This value represents the value of the consequent associated with Rule 5 for ANFIS module 2, which was determined using the first-order polynomial in terms of weight (77.15 kg), BMI (25.1918 kg.m^{-2}), and HR_{rest} (57.17 bpm), see Rule 5 in Appendix B:
-0.35439 x (77.15)+0.73869 x (25.1918)+1.5339 x (57.17)-19.538.

This value represents the weighted value of the consequent associated with Rule 8 using the product implication method:
(59.42283238) x (0.034553285).

ANFIS module 3

Rule base	Antecedent						Consequent			
	Fuzzification (Age)	Fuzzification (Weight)	Fuzzification (Height)	Fuzzification (BMI)	Fuzzification (HR_{rest})	Firing strength	Unweighted (slope)	Unweighted (intercept)	Weighted (slope)	Weighted (intercept)
Rule 1	7.19954E-05	0.829266712	0.831293076	0.52618957	0.038180434	9.97094E-07	0.346055224	-13.1206899	3.4505E-07	-1.30826E-05
Rule 2	2.56895E-05	0.987057882	0.696174577	0.93878427	0.248349669	4.11572E-06	0.464396139	-25.00245156	1.91133E-06	-0.000102903

Figure H-6: Weighted output associated with each rule of the ANFIS modules

5. Aggregate the consequents across all rules for each ANFIS module.

The final aggregated output of an ANFIS module is calculated as the weighted average of all the rules' outputs belonging to this module. Four aggregated outputs are produced corresponding to the Flex-HR parameters (Figure H-7).

ANFIS module 1

Rule base	Antecedent				→	Consequent	
	Fuzzification (Age)	Fuzzification (Weight)	Fuzzification (Height)	Fuzzification (HR_{rest})	Firing strength	Unweighted	Weighted
Rule 1	0.004921499	0.981463782	0.94059947	0.57512295	0.002612986	5.2268565	0.013657703
Rule 2	6.89463E-06	0.998419793	0.999001681	0.89267856	6.13883E-06	9.0549161	5.55865E-05

Estimated VO_2 rest
5.235828882 ml/kg.min

This value is calculated as the sum of all weighted outputs/sum of all firing strengths.

ANFIS module 2

Rule base	Antecedent			→	Consequent	
	Fuzzification (Weight)	Fuzzification (BMI)	Fuzzification (HR_{rest})	Firing strength	Unweighed	Weighted
Rule 1	0.495723032	0.561067048	1.49024E-10	4.14485E-11	49.57285208	2.05472E-09
Rule 2	0.996368926	0.998738116	0.72328131	0.719745639	74.67061172	53.74384714
Rule 3	0.002681666	0.055969537	0.023512159	3.52898E-06	29.93927758	0.000105655
Rule 4	0.24008949	0.762755591	3.17199E-05	5.80886E-06	57.60490136	0.000334619
Rule 5	0.711245841	0.322904118	0.150451326	0.034553285	59.42283238	2.053254072

Estimated Flex point
73.97180212 bpm

This value is calculated as the sum of all weighted outputs/sum of all firing strengths.

This value is calculated as the sum of all weighted outputs (slope)/sum of all firing strengths.

ANFIS module 3

Rule base	Antecedent					→	Consequent			
	Fuzzification (Age)	Fuzzification (Weight)	Fuzzification (Height)	Fuzzification (BMI)	Fuzzification (HR_{rest})	Firing strength	Unweighted (slope)	Unweighted (intercept)	Weighted (slope)	Weighted (intercept)
Rule 1	7.19954E-05	0.829266712	0.831293076	0.52618957	0.038180434	9.97094E-07	0.346055224	-13.1206899	3.4505E-07	-1.30826E-05
Rule 2	2.56895E-05	0.987057882	0.696174577	0.93878427	0.248349669	4.11572E-06	0.464396139	-25.00245156	1.91133E-06	-0.000102903

Estimated slope	Estimated intercept
0.441317462	-22.68528728

This value is calculated as the sum of all weighted outputs (intercept)/sum of all firing strengths.

Figure H-7: Estimated Flex-HR parameters by the three ANFIS modules

6. Develop the calibration curve.

An individual's calibration curve is developed based on the estimated Flex-HR parameters (Figure H-8). The calibration curve is used to estimate the individual's VO_2 values based on field HR measurements.

Estimated Flex-HR parameters

Estimated VO_2 rest	5.235828882	ml/kg.min
Estimated Flex point	73.97180212	bpm
Estimated slope	0.441317462	
Estimated intercept	-22.68528728	

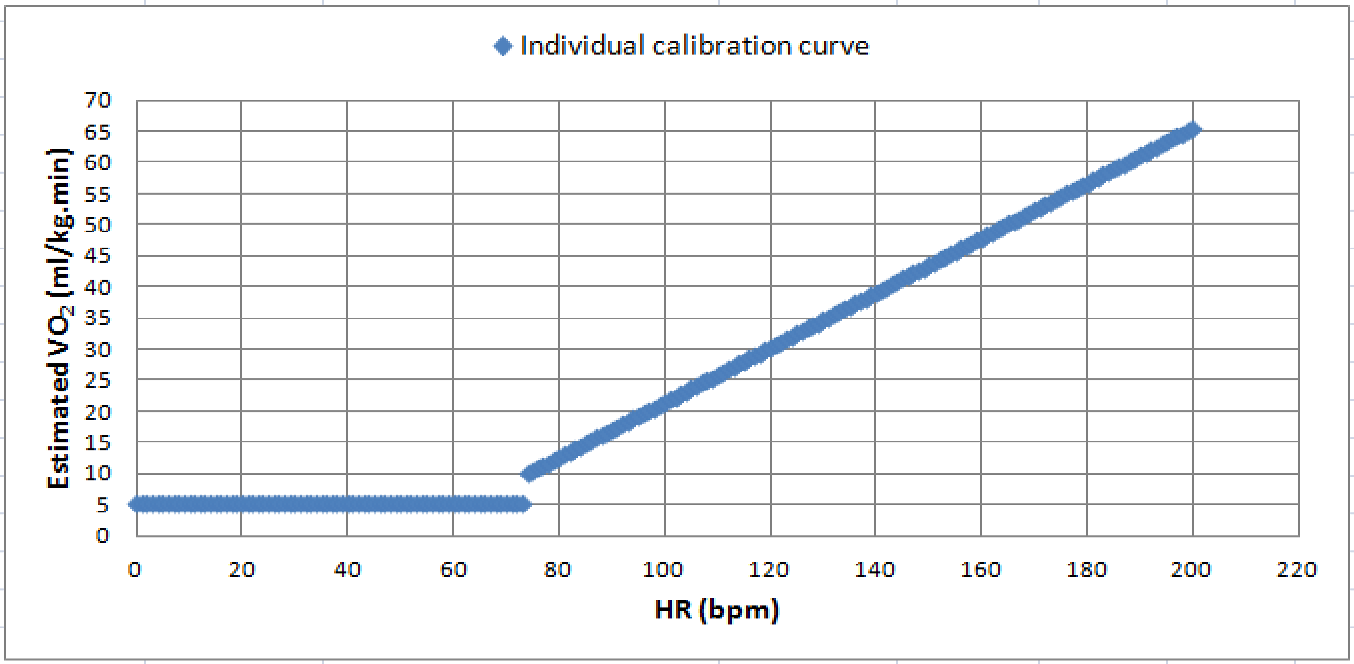


Figure H-8: Estimated individual calibration curve

APPENDIX I – An example of developing fuzzy IF-THEN rules

For example, applying the subtractive clustering algorithm to a data group associated with the heavy work rate category, if the cluster center $x_i^* = (HR^*, HR_{max}^*, HR_{rest}^*, \text{body weight}^*)^T$ was determined for that data group, then the associated fuzzy rule can be written as follows:

$$Rule\ i: IF\ \{x\ is\ near\ x_i^*\}\ THEN\ class\ is\ H$$

where x is a new input vector $(HR, HR_{max}, HR_{rest}, \text{body weight})^T$. The degree of fulfillment of the premise $\{x\ is\ near\ x_i^*\}$ is defined as:

$$\mu_i = e^{-\alpha\|x-x_i^*\|^2} \qquad (I.1)$$

where $\alpha = 4/r_a^2$ and r_a is a positive constant indicating cluster radius. The part $\{class\ is\ H\}$ is called the consequent. This rule can be further written in the following form:

$$Rule\ i: IF\ HR\ is\ A_{i1}\ AND\ HR_{max}\ is\ A_{i2}\ AND\ HR_{rest}\ is\ A_{i3}\ AND\ body\ weight\ is\ A_{i4}\ THEN\ class\ is\ H$$

where A_{ij} is the membership function associated with the *j*th input variable in the *i*th rule. The membership function A_{ij} is written as:

$$A_{ij}(X_j) = exp\left\{-\frac{1}{2}\left(\frac{X_j - x_{ij}^*}{\sigma_{ij}}\right)^2\right\} \qquad (I.2)$$

$$\sigma_{ij}^2 = \frac{1}{2\alpha} \qquad (I.3)$$

where X_j is the *j*th input variable (*j*=1, 2, 3, and 4 associated with inputs HR, HR_{max}, HR_{rest}, and body weight, respectively) and x_{ij}^* is the *j*th element of x_i^*.

APPENDIX J – Description of the backward selection method

Consider the set of potential input variables in the following order: HR during activity, HR_{max}, HR_{rest}, BR, BMI, and body weight. The set {i} represents the set of input variables after removing the *i*th input variable, where i =1, 2, 3, 4, 5, and 6 corresponds to HR, HR_{max}, HR_{rest}, BR, BMI, and body weight, respectively. The set {0} represents the full set of all potential input variables. The input selection procedure was adapted from Chiu (1996), as follows:

1. Develop an initial fuzzy classifier using the training dataset and incorporating the set of all potential input variables (level 0: {0}={HR during activity, HR_{max}, HR_{rest}, BR, BMI, and body weight}) based on the method described in Section 2.3 and then assess its performance using the test dataset.
2. Temporarily remove each input variable from the set of potential variables, one at a time (e.g., level 1: {1}, {2}, {3}, {4}, {5}, and {6}) from the rule-base of the fuzzy classifier and assess the resultant truncated fuzzy classifiers using the test dataset.
3. If there is improvement over a previous level, permanently remove the input variable associated with the best performance obtained in step 2. Identify the best set of input variables associated with the best truncated fuzzy classifier and its corresponding performance. If there is no improvement, go to step 5.
4. If there is another input variable remaining in the best truncated fuzzy classifier, go to step 2. Otherwise, go to step 5.
5. Of the initial and the best truncated fuzzy classifiers at different levels, select the set of input variables associated with the best performance.

APPENDIX K – The proposed ANFIS classifier

The developed ANFIS classifier consists of the following 8 fuzzy IF-THEN rules:

$$IF\ \%HR_{max}\ is\ A_1\ AND\ HR_{rest}\ is\ B_1\ AND\ Body\ weight\ is\ C_1\ THEN\ \%VO_{2max} = 3.017 \times (\%HR_{max}) + 7.963 \times (HR_{rest}) - 15.04 \times (2.205 \times Body\ weight) + 1650$$

$$IF\ \%HR_{max}\ is\ A_2\ AND\ HR_{rest}\ is\ B_2\ AND\ Body\ weight\ is\ C_2\ THEN\ \%VO_{2max} = -1.53 \times (\%HR_{max}) - 3.668 \times (HR_{rest}) + 4.595 \times (2.205 \times Body\ weight) - 394.8$$

$$IF\ \%HR_{max}\ is\ A_3\ AND\ HR_{rest}\ is\ B_3\ AND\ Body\ weight\ is\ C_3\ THEN\ \%VO_{2max} = 1.098 \times (\%HR_{max}) - 0.335 \times (HR_{rest}) - 0.037 \times (2.205 \times Body\ weight) + 1.093$$

$$IF\ \%HR_{max}\ is\ A_4\ AND\ HR_{rest}\ is\ B_4\ AND\ Body\ weight\ is\ C_4\ THEN\ \%VO_{2max} = 25.19 \times (\%HR_{max}) - 3.846 \times (HR_{rest}) + 5.165 \times (2.205 \times Body\ weight) - 1769$$

$$IF\ \%HR_{max}\ is\ A_5\ AND\ HR_{rest}\ is\ B_5\ AND\ Body\ weight\ is\ C_5\ THEN\ \%VO_{2max} = 1.922 \times (\%HR_{max}) + 71.59 \times (HR_{rest}) - 16.19 \times (2.205 \times Body\ weight) - 4224$$

$$IF\ \%HR_{max}\ is\ A_6\ AND\ HR_{rest}\ is\ B_6\ AND\ Body\ weight\ is\ C_6\ THEN\ \%VO_{2max} = 3.864 \times (\%HR_{max}) + 54.63 \times (HR_{rest}) - 12.21 \times (2.205 \times Body\ weight) - 3154$$

$$IF\ \%HR_{max}\ is\ A_7\ AND\ HR_{rest}\ is\ B_7\ AND\ Body\ weight\ is\ C_7\ THEN\ \%VO_{2max} = 3.735 \times (\%HR_{max}) + 20.96 \times (HR_{rest}) - 1.445 \times (2.205 \times Body\ weight) - 1485$$

$$IF\ \%HR_{max}\ is\ A_8\ AND\ HR_{rest}\ is\ B_8\ AND\ Body\ weight\ is\ C_8\ THEN\ \%VO_{2max} = -9.785 \times (\%HR_{max}) - 0.7 \times (HR_{rest}) - 0.819 \times (2.205 \times Body\ weight) + 787.4$$

The parameters associated with the Gaussian membership functions describing the fuzzy sets for the three input variables (%HR_{max}, HR_{rest}, and body weight) are summarized in Table K.1.

Table K.1: Optimized parameters describing the Gaussian membership functions associated with different input variables

Fuzzy Rule	**Fuzzy sets associated with %HR_{max} (A_i)**		**Fuzzy sets associated with HR_{rest} (B_i)**		**Fuzzy sets associated with body weight (C_i)**	
	μ_{A_i}	σ_{A_i}	μ_{B_i}	σ_{B_i}	μ_{C_i}	σ_{C_i}
Rule 1	56.38	9.1624	83.682	9.5545	72.3	1.69
Rule 2	53.342	2.4924	95.321	6.9145	80.06	5.99
Rule 3	53.532	15.663	83.907	13.06	71.58	7.68
Rule 4	64.384	9.6039	83.018	9.2297	68.84	7.26
Rule 5	69.431	8.9314	91.307	8.233	71.65	6.68
Rule 6	89.484	8.0047	94.887	5.4539	80.78	6.41
Rule 7	70.139	9.9663	81.694	6.3138	78.85	5.34
Rule 8	62.162	8.93	70.724	5.632	68.34	5.05

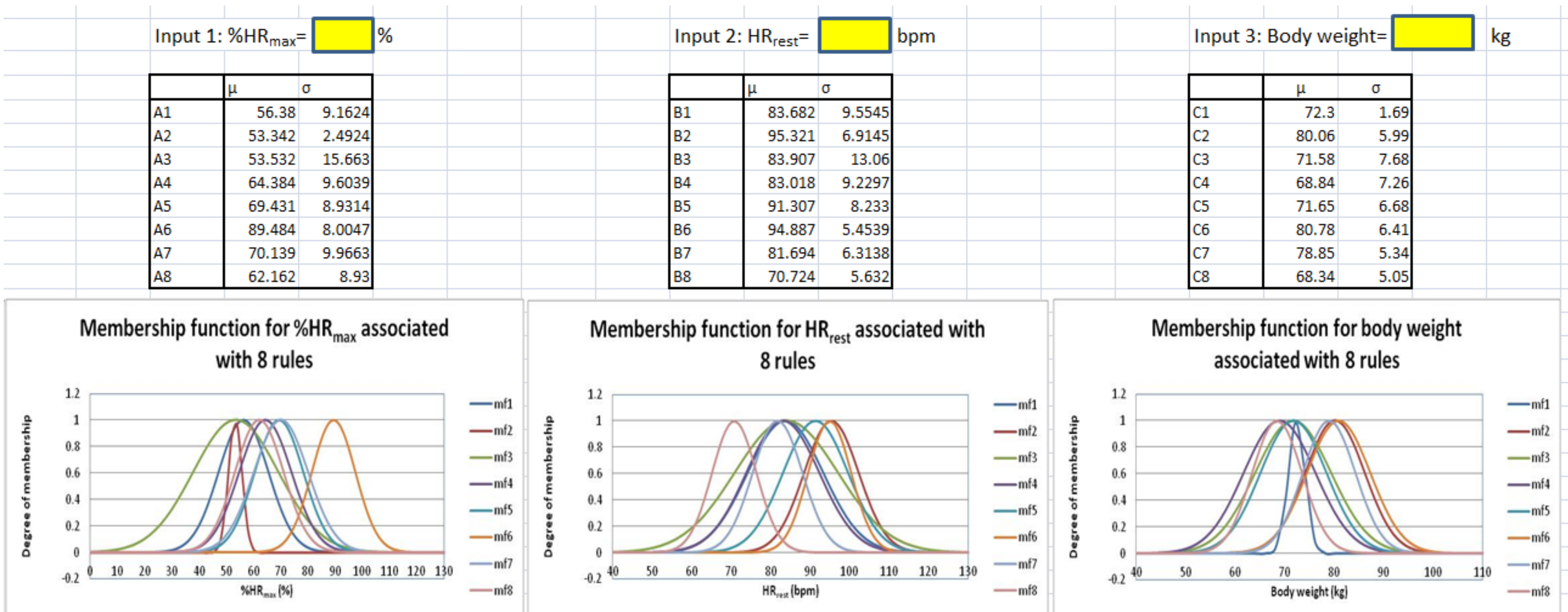
Note. A_i: fuzzy sets of %HR_{max} associated with Rule i (i = 1, …, 8); B_i: fuzzy sets of HR_{rest} associated with Rule i (i = 1, …, 8); C_i: fuzzy sets of body weight associated with Rule i (i = 1, …, 8).

APPENDIX L – Implementing the ANFIS classifier using Excel

Once the ANFIS classifier has been developed using MATLAB (Appendix K), it can be implemented in Excel as a decision-making tool, following five main steps:

1. Determine the input variables and associated membership functions.

The first step is to determine the variables to be input into the ANFIS classifier (%HR_{max}, HR_{rest}, and body weight). Then, define the predetermined Gaussian membership functions for each input variable using the "Exp ()" function provided in Excel (Figure L-1).



Input 1: %HR_{max}= %

	μ	σ
A1	56.38	9.1624
A2	53.342	2.4924
A3	53.532	15.663
A4	64.384	9.6039
A5	69.431	8.9314
A6	89.484	8.0047
A7	70.139	9.9663
A8	62.162	8.93

Input 2: HR_{rest}= bpm

	μ	σ
B1	83.682	9.5545
B2	95.321	6.9145
B3	83.907	13.06
B4	83.018	9.2297
B5	91.307	8.233
B6	94.887	5.4539
B7	81.694	6.3138
B8	70.724	5.632

Input 3: Body weight= kg

	μ	σ
C1	72.3	1.69
C2	80.06	5.99
C3	71.58	7.68
C4	68.84	7.26
C5	71.65	6.68
C6	80.78	6.41
C7	78.85	5.34
C8	68.34	5.05

Figure L-1: Defining the membership functions (mf) associated with %HR_{max}, HR_{rest}, and body weight in Excel

2. Fuzzify the input variables.

In the fuzzification process, the degree to which each input variable belongs to each of the associated fuzzy sets is determined using the predetermined membership functions. This yields a fuzzified value for each input variable between 0 and 1 (Figure L-2).

Parameters associated with $\%HR_{max}$			Parameters associated with HR_{rest}			Parameters associated with body weight		
MF	μ	σ	MF	μ	σ	MF	μ	σ
A1	56.38	9.1624	B1	83.682	9.5545	C1	72.3	1.69
A2	53.342	2.4924	B2	95.321	6.9145	C2	80.06	5.99
A3	53.532	15.663	B3	83.907	13.06	C3	71.58	7.68
A4	64.384	9.6039	B4	83.018	9.2297	C4	68.84	7.26
A5	69.431	8.9314	B5	91.307	8.233	C5	71.65	6.68
A6	89.484	8.0047	B6	94.887	5.4539	C6	80.78	6.41
A7	70.139	9.9663	B7	81.694	6.3138	C7	78.85	5.34
A8	62.162	8.93	B8	70.724	5.632	C8	68.34	5.05

	Antecedent		
Rule base	Fuzzification ($\%HR_{max}$)	Fuzzification (HR_{rest})	Fuzzification (Body weight)
Rule 1	0.24286633	0.723812198	0.987087293
Rule 2	1.25102E-12	0.020161498	0.458104259
Rule 3	0.506736498	0.832537806	0.991602334
Rule 4	0.742506497	0.748950534	0.876021889
Rule 5	0.965581228	0.177575585	0.990447958
Rule 6	0.087012589	0.002488	0.440282489
Rule 7	0.986292388	0.66587564	0.50146565
Rule 8	0.558887765	0.644817764	0.703513421

This value represents the fuzzified value of %HRmax = 71.79% associated with Rule 8, according to the predetermined Gaussian function: Exp(-0.5*((71.79-62.162)/8.93)^2).

This value represents the fuzzified value of body weight = 72.57 kg associated with Rule 8, according to the predetermined Gaussian function: Exp(-0.5*((72.57-68.34)/5.05)^2).

This value represents the fuzzified value of HRrest = 76 bpm associated with Rule 8, according to the predetermined Gaussian function: Exp(-0.5*((76-70.724)/5.632)^2).

Figure L-2: Input variable fuzzification

3. Determine the firing strength of each rule.

Fuzzifying the input variables yields the degree to which each input variable is satisfied for each rule. Because there are more than one input variable in the antecedent of the rules, the fuzzy operator (i.e., product) is used to obtain a number (the firing strength) associated with the antecedent of each rule (Figure L-3).

	Antecedent			------------------------>
Rule base	Fuzzification (%HR_{max})	Fuzzification (HR_{rest})	Fuzzification (Body weight)	Firing strength (Product operator)
Rule 1	0.24286633	0.723812198	0.987087293	0.173519693
Rule 2	1.25102E-12	0.020161498	0.458104259	1.15545E-14
Rule 3	0.506736498	0.832537806	0.991602334	0.418334507
Rule 4	0.742506497	0.748950534	0.876021889	0.487156331
Rule 5	0.965581228	0.177575585	0.990447958	0.169825823
Rule 6	0.087012589	0.002488	0.440282489	9.53156E-05
Rule 7	0.986292388	0.66587564	0.50146565	0.329336601
Rule 8	0.558887765	0.644817764	0.703513421	0.2535327

This value represents a single antecedent value (firing strength) of Rule 8, which was calculated according to the product operator: (0.558887765) x (0.644817764) x (0.703513421).

Figure L-3: Determining the firing strength associated with each rule

4. Determine the weighted output of each rule.

The consequent (output) of a fuzzy rule is calculated as a function of the input variables. The output value is then rescaled using the firing strength of that rule. This process (implication) is applied to each rule using the product method (Figure L-4).

	Antecedent			···········>	Consequent	
Rule base	Fuzzification (%HR_{max})	Fuzzification (HR_{rest})	Fuzzification (Body weight)	Firing strength (Product operator)	Unweighted output	Weighted output
Rule 1	0.24286633	0.723812198	0.987087293	0.173519693	65.39312821	11.34699551
Rule 2	1.25102E-12	0.020161498	0.458104259	1.15545E-14	-47.99876923	-5.54603E-13
Rule 3	0.506736498	0.832537806	0.991602334	0.418334507	48.53496923	20.30385245
Rule 4	0.742506497	0.748950534	0.876021889	0.487156331	573.6168205	279.4410658
Rule 5	0.965581228	0.177575585	0.990447958	0.169825823	-1235.570256	-209.8317362
Rule 6	0.087012589	0.002488	0.440282489	9.53156E-05	-678.3046154	-0.064652994
Rule 7	0.986292388	0.66587564	0.50146565	0.329336601	144.9138462	47.7254335
Rule 8	0.558887765	0.644817764	0.703513421	0.2535327	-99.31842051	-25.18046735

This value represents the value of the consequent associated with Rule 8, which was determined using the first-order polynomial in terms of %HRmax (71.79%), HRrest (76 bpm), and body weight (72.57 kg), see Rule 8 in Appendix A:
-9.785 x (71.79)-0.7006 x (76)-0.8185 x [(72.57) x (2.205)]+787.4.

This value represents the weighted value of the consequent associated with Rule 8 using the product implication method:
(-99.31842051) x (0.2535327).

Figure L-4: Determining the weighted output associated with each rule

5. Aggregate the consequents across all rules.

The final aggregated output is calculated as the weighted average of all the rules' outputs. This value represents an estimate of the relative workload (%VO_{2max}) by which work rate is determined based on the norms provided by the U.S. Department of Health and Human Services (1996) (Figure L-5).

	Antecedent			→	Consequent	
Rule base	Fuzzification (%HR_{max})	Fuzzification (HR_{rest})	Fuzzification (Body weight)	Firing strength (Product operator)	Unweighted output	Weighted output
Rule 1	0.24286633	0.723812198	0.987087293	0.173519693	65.39312821	11.34699551
Rule 2	1.25102E-12	0.020161498	0.458104259	1.15545E-14	-47.99876923	-5.54603E-13
Rule 3	0.506736498	0.832537806	0.991602334	0.418334507	48.53496923	20.30385245
Rule 4	0.742506497	0.748950534	0.876021889	0.487156331	573.6168205	279.4410658
Rule 5	0.965581228	0.177575585	0.990447958	0.169825823	-1235.570256	-209.8317362
Rule 6	0.087012589	0.002488	0.440282489	9.53156E-05	-678.3046154	-0.064652994
Rule 7	0.986292388	0.66587564	0.50146565	0.329336601	144.9138462	47.7254335
Rule 8	0.558887765	0.644817764	0.703513421	0.2535327	-99.31842051	-25.18046735

This value is calculated as the sum of all weighted outputs/sum of all firing strengths.

Estimated %VO_{2max}	**67.55127473**	**%**
Estimated work rate	**Heavy**	**Category**

The category is determined based on work rate norms determined by the U.S. Department of Health and Human Services (1996).

Figure L-5: Estimated %VO_{2max} and work rate category